

MARKUPS, ENDOGENOUS MARKET POWER AND  
MISALLOCATION IN TURKEY

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MARKUPS, ENDOGENOUS MARKET POWER AND  
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## ABSTRACT

### Markups, Endogenous Market Power and Misallocation in Turkey

Analyzing firms' market power and the related aggregate misallocation is one of the intriguing subjects of the macroeconomics research frontier. However, market power and misallocation are mostly treated as exogenous factors, and the literature mostly focus on the effects of the exogenous variation in misallocation on aggregate economic outcomes (Hsieh and Klenow (2009), Restuccia and Rogerson (2008), Fattal Jaef (2018)). Nonetheless, Peters (2020) built up a model with endogenous misallocation where firm's market power is endogenously determined and via interrelated dynamics of the model, and the equilibrium distribution of markups emerges in the form of a Pareto distribution through which the impact of the market power can be explicitly observed. In this thesis, I will apply the model of Peters (2020) to Turkey, and I will use different samples in terms of the firm size and technology levels. The aim of this study is to reveal if there is any misallocation that is coming from potentially excessive level of market power, and to understand the implications of the market power in the aggregate outcomes. Furthermore, a counterfactual analysis will be done to understand what would happen if the entry barriers in Turkey become weaker, so that the Turkish economy will resemble a more competitive setting. Usually considered an emerging economy, this analysis will be fundamental to understanding the creative destruction related dynamics in Turkey.

## ÖZET

### Mark-uplar, Endojen Market Gücü ve Türkiye’de Kaynakların Yanlış Tahsisi

Firmaların market gücünü ve ilgili toplu yanlış tahsisi analiz etmek, makroekonomi araştırmaları içerisinde ilgi çekici konulardan biri. Ancak piyasa gücü ve yanlış tahsis çoğunlukla ekzojen faktörler olarak ele alınmış ve literatür genel olarak yanlış tahsiste oluşacak olan ekzojen sapmaların etkisine odaklanmıştır (Hsieh and Klenow (2009), Restuccia and Rogerson (2008), Fattal Jaef (2018)). Bununla birlikte, Peters (2020) endojen şekilde yanlış tahsisi belirleyen bir model oluşturmuştur. Firmaların market gücü de endojen olarak ve modeldeki birbiriyle ilişkili dinamikler aracılığıyla belirlenir. Sonuç olarak mark-upların dengedeki dağılımı Pareto formunda olur ve bu dağılımın biçim parametresi doğrudan market gücünün etkisini göstermektedir. Bu tezde Peters (2020) modelini Türkiye ekonomisi için uygulayacağım ve bunu yaparken firma büyüklüğü, teknoloji seviyeleri farklı olan firma örneklemelerini kullanacağım. Bu çalışmanın amacı, Türkiye’deki firmalar için fazla miktarda market gücünden kaynaklanan herhangi bir yanlış dağıtım olup olmadığını ortaya çıkarmaktır ve sonrasında da market gücünün ekonomi çapındaki sonuçlara etkisini incelemektir. Ayrıca, karşı olgusal bir analiz Türkiye’ye giriş engelleri ortadan kalkarsa ne olacağını anlamak için kullanılacaktır. Bu analizde Türkiye ekonomisi daha rekabetçi bir market yapısına bürünecektir. Genellikle yükselen bir ekonomi olarak kabul edilen Türkiye için bu analiz yaratıcı yıkım ile alakalı dinamikleri anlamak için kritik öneme sahip olabilir.

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## CHAPTER 1

### INTRODUCTION

Recent literature tackles the problems related to declining business dynamism and the factors that boost or slow down an economy. One result that commonly manifests itself as a valid concern is the firms' increasing market power and increasing manipulation of the overall market dynamics. Especially the winner-take-all type of market structure enables firms' to perform their market power almost entirely. A clear indicator of this market power is the markup behavior of firms. Intuitively, increasing markups would signal higher power accumulation which would also hold theoretically in this study. However, one step forward in this argument would be a question in the form of what is the cost of this market power if it indeed exists. This question is addressed differently within the literature. However, in this thesis, I will use a novel model to highlight the possible misallocation due to market power, which is also endogenously determined. Hence, there will be a clear connection between the markups, misallocation, and the resulting aggregate misallocation. Regarding the misallocation, aggregate losses in TFP and labor share would be the focal points. However, we will need a solid theoretical basis to reveal such complex relations.

As one of the workhorse models in heterogeneous firm analysis, the Schumpeterian framework is commonly adopted to analyze winner-take-all markets. Such creative destruction based modeling allows for a market structure where firms continuously compete to gain market power the profits. In a simplified setting, two firms compete to acquire the leader status in each production line. The leader of each production line is the sole producer of their market, so the monopolist of it. In order to gain the leadership position, a follower firm must destroy the leader, and doing it creatively requires innovation or being more efficient (more productive or cost-efficient) in producing a product, simply holding a right to produce something.

In contrast, excluding others from producing it gives a monopolistic nature to the creative destruction paradigm. Naturally, the R&D sector enables such a

hierarchy to occur via patenting. Since a firm's power over another relies on its production technology, some creative destruction models rely on process patents, which are different from product patents. Process patents are related to innovation in the production process of a product.

On the other hand, product innovations (Grossman and Helpman (1991)) are related to patenting the product itself. For neatness, process patents better suit the model that I will argue over. In Layman's terms, firms compete over finding a cheaper way to produce a product from a given set of products, so they do not come up with new products but rather with more efficient ways to produce them. Such models focus on price competition in a given sector, and the monopoly power comes from the fact that the more productive firms have the least costly producing methods. This cost-effectiveness enables them to eliminate their competitor via Bertrand competition. Due to limit pricing, a follower's optimal strategy is not to produce if it is less productive because it can only have negative profits under this price competition scheme.

Moreover, every intermediate good in the market is unique in this simplified setting. Intermediate goods cannot be substituted in the production process, so the demand for an intermediate good is not directly affected by the changes in the prices of other intermediate goods. On the other hand, perfect substitution exists for a given product among competing firms. Since the final good producer produces the final good using a continuum of intermediate goods (not substitutable), it needs to devote the same amount to each intermediate good. The demand of a final good producer for any intermediate good solely depends on the respective price of that intermediate good. Hence, if a firm captures a market through a more productive way of producing an intermediate good, it will not be affected by the dynamics of the economy's other production lines, which also complements the monopolistic power of a leader.

The model follows the Schumpeterian creative destruction paradigm and builds on the seminal paper of Klette and Kortum (2004), where firms extend their production lines horizontally to capture new product lines. One novelty of Peters

(2020) is that it adds an own-innovation channel to the original model so that firms can capture higher markups by increasing the productivity gap with the followers. The intuition comes from the Bertrand competition; that is, firms compete over the prices for given quantities. Hence, due to limit pricing, the more productive firm will exploit its advantage in cost efficiency and capture the whole market by pricing the product to the marginal cost of the less productive firm. On the other hand, successfully expanding a firm to a new product line resets the productivity gap in that line so that the productivity gap turns out to be unity.

Peters (2020) brings another novel contribution by explaining some wedges in the economy through the distribution of markups. Hence, the purpose of the author is to determine how much of those wedges (in labor share and TFP) is coming from the markups if the misallocation is caused by only markups, so the distortion that is created by the markups becomes visible. To do so, the author exploits the fact that markups have a unique Pareto distribution at the equilibrium. This distribution's tail parameter can explain the results of market power in terms of misallocation. Hence, the definition of market power in this setting is tied up with a firm's power to manipulate the prices of its products. At the same time, this tail parameter is endogenous to and determined by a statistic that the author called churning intensity, which is the rate at which creative destruction occurs in the economy over the innovation by incumbent firms.

Therefore, the distribution of markups would be shaped by two different channels. Firms' successful own innovations let them to take a higher portion of markups from the overall sales. On the other hand, they can extend to new markets, which would reduce the average markups. Similarly, a firm can lose a production line if another firm makes a successful expansion to that sector which known as incumbent creative destruction. Overall, the clash between the above channels would dictate how the markup distribution emerges as an equilibrium outcome, which would be linked to an endogenously determined statistic, churning intensity.

Most of the data in this study come from the Entrepreneurship Information System (EIS), which is a comprehensive data set that includes 8 different data sources and was created by the Ministry of Industry and Technology. Quantitative analysis is done chiefly for three different samples. In all samples, the prerequisite for the firms is that they have at least one worker and incur positive material costs to be included in samples. This step is done to eliminate possible anomalies related to the data set as well as to include only economically active firms in the samples. The first sample is basically including all the firms that satisfy the above conditions. The second sample captures the firms with at least 50 workers and also have at least one 250 Million Dollar item in their financial statement. This specification comes from the Small and Medium Enterprises (SME) 's recently updated definition and ensures that we have medium-scaled and above firms for this sample. The last sample is formed over the technology levels, and this sample only includes firms that operate in manufacturing sector and are denoted as medium-high or high in terms of the technology level.

Empirical results show a clear relation between the markups and cohort age, as the theory predicted. The theory suggests that as firms get older, they can accumulate more market power so that they can raise markups. Regarding the firm age and average log markup, all specifications show a clear trend that is increasing with age. Moreover, regression results also support this argument. Especially the specification with the firms that have more than 50+ workers had some striking results in terms of the impact of age on markup growth. Accordingly, after controlling for the inputs together with the time and industry fixed effects, bigger sized firms increased their markups on average by more than 3% per year. In contrast, the corresponding value for the high tech firm sample is around 1.8%. The reasons which can result in such a difference are highlighted in the empirical analysis part. However, it might highlight the result of market power as well as lack of controls such as capital.

The model provides a direct mapping from the observations to the moments, and the theoretical background will be analyzed later in detail. By calibrating the

model, we find the parameters that will satisfy the data implied outcomes (moments). The results that we get via the calibration also resemble regression results. The samples with technologically advanced firms give the highest values for the efficiency related parameters. In contrast, the sample with 50+ workers has quiet worrisome results in terms of business dynamism and efficiency.

The markups and misallocation relation is highlighted through two endogenous statistics, misallocation in aggregate TFP and labor wedge. The model implies that the samples with all firms and high tech firms have similar results regarding the impact of the market power. Both samples indicate average markups of around 20%, and the losses due to misallocation are very similar. The misallocation in aggregate TFP is around 1.3% and the misallocation in the labor share is around 15%. The reasons for the massive difference in misallocation channels will be explained in the model part. On the other hand, in the sample with larger firms, the TFP loss is around 3%, and the labor wedge is around 21.5%. Hence, the burden of market power on the overall economy can be clearly observed through the decreasing labor shares; again, the impact of misallocation that is coming from markups is more striking for the larger firms.

Lastly, the counterfactual analysis is done to highlight the significance of market barriers. Two model parameters are recalibrated (entry and expansion efficiency) to match entry rates and employment growth of the U.S. economy. This newly simulated economy is named the U.S. The results show that having fewer market barriers and a more competitive environment has a huge impact on the model. Especially, the number of firms decreased by almost 64%, and all markup related dynamics cooled down too. Misallocation channels also got better off. Even though this result implies a market concentration, as pointed out by Syverson (2004a), Syverson (2004b), and Syverson (2019), market concentration does not necessarily imply higher market power, and our model clearly serves this end. In our model, there would be a relatively small amount of firms that are bigger in size for the U.S. economy. However, the economy acts more efficiently as markups go down and

misallocation becomes less of a threat. Moreover, there is a slight increase in aggregate growth rate too.

To sum up, in this thesis, I will use the model of Peters (2020) for the Turkish economy and do so with different samples. The following section will briefly go over the related literature. Next, the model will be explained in detail, which is followed by the static and dynamic equilibrium results. Then, in the quantitative analysis part, regression analysis on the markups and cohort age relation will be done with the calibration of the model and counterfactual analysis. Lastly, the conclusion section will make a wrap-up.

## CHAPTER 2

### RELATED LITERATURE

Two main building blocks will be highlighted in this section. The first pillar is related to the studies that tackle business dynamism related issues, especially with the availability of detailed firm-level data; empirical studies in this class have been experiencing a rapid boost. Secondly, the knowledge diffusion related models that focus on the learning dynamics between individuals, firms etc. will be overviewed.

For clarity, it would be useful to overview the basics of Schumpeterian framework. When compared to their predecessors (Lucas (1988), Romer (1990)), where the market power related dynamics are not fully internalized, Aghion and Howitt (1992) and Grossman and Helpman (1991) introduced the Schumpeterian paradigm to the endogenous growth models. Allowing firms to compete in monopolistic industries where the leader firm obtains all the market power and available profits, whereas followers try to compete with the leader to steal the market power, brings a unique approach to the newly emerging endogenous growth literature. Another elegant aspect of those models is that a follower firm reflects the behavior of all follower firms in their respective industries. Hence, having a race-type model with two firms is quite explanatory for this model type. However, one drawback of first generation of Schumpeterian models is that due to Arrow replacement effect, there is no incumbent innovation at the equilibrium. Due to the creative destruction, incumbent firms lose incentive to innovate, and only entrant firms innovate at the equilibrium. As meaningful as it is, recent studies also indicate potential benefits in the process of creative destruction to the so-called destructed side, which will be an argument that will be extended later.

Klette and Kortum (2004) extends the framework of Aghion and Howitt (1992) by adjusting the model to explain firm dynamics. Moreover, in the setting of Klette and Kortum (2004), incumbent firms also innovate at the equilibrium which is a salient feature of the model. However, incumbent innovation do not take a form of

producing a completely new product, or a result of strategic interactions between the other incumbent firms in a product line. Rather, firms randomly extends to other product lines with a given Poisson rate, which enables them to live longer by escaping from creative destruction for a longer duration. However, since firms do not make product improvements this sort of incumbent innovation does not fully capture the strategic interactions at the firm level. On the other hand, Peters (2020) extends the framework of Klette and Kortum (2004) by embedding the firm level strategic interactions to the model of Klette and Kortum (2004) through adding a own-innovation channel. Thus, in Peters (2020), incumbent firms' innovation is changing its form from a random process to a path of accumulating market power. Existing firms innovate to increase the productivity gap which gives them more market power, in return raising the markups due to Bertrand competition.

This study can be considered as an alternative to understand the business dynamism in Turkey through a parsimonious model. Even though there are not many studies conducted in Turkey, various studies focus on different channels that can be attributed to the slowdown of the business dynamism in the U.S. economy. Among others, some channels get more attention by scholars, such as increasing markups (Barkai (2020), De Loecker, Eeckhout, and Unger (2020), Edmond, Midrigan, and Xu (2022)), rising market concentration and emergence of superstar firms (Autor, Dorn, Katz, Patterson, and Van Reenen (2017), Autor, Dorn, Katz, Patterson, and Van Reenen (2020), Eggertsson, Robbins, and Wold (2018)), and decline in the labor share of output (Hopenhayn, Neira, and Singhania (2018), Karabarbounis and Neiman (2014)). In this thesis, the above channels tried to be highlighted for Turkey.

The focal analysis will be done through the effect of markups on the aggregate economy. However, markups are not observable items of the balance sheets or financial statements in Turkey. Nevertheless, there is a vast literature on measuring the markups, both in terms of the theory and empirical results in terms of the aggregate estimates (De Loecker and Warzynski (2012), De Loecker, Goldberg, Khandelwal, and Pavcnik (2016), De Loecker et al. (2020), De Ridder, Grassi, and

Morzenti (2022)). Peters (2020) found an average markup estimate of around 12% for the period between 1990 and 1998 for the Indonesian economy. However, De Loecker et al. (2020) showed that the markups are changing significantly in recent decades. Especially, the authors pointed out that the firms in U.S. who are open to public trade has increased their average markups from 20% to 60% between 1980 and 2012.

The literature previous to Peters (2020) considers the impact of market power as an exogenous phenomena. Moreover, how the misallocation affects the aggregate outcomes is also approached through exogenous variations in these misallocation channels. On the other hand, Peters (2020) introduced the market power as an endogenous process, which is determined by the strategic interactions of the firms at the aggregate level. Moreover, at the equilibrium, markups have a unique Pareto distribution that the shape parameter of this distribution can fully explain the aggregate cost of the market power in terms of the aggregate misallocation in TFP and labor wedge. Furthermore, the distribution of markups is also determined endogenously. The process that creates this dynamic structure for this model is the conflict between the own-innovation and creative destruction. The own-innovation channels serve for the firms' power accumulation purposes, whereas creative destruction acts as a competitive force in this model. Therefore, the long run clash between these two forces will be the source of the Pareto distribution for the markups given that a firm can operate in multiple product lines at the same time. Among others, De Loecker et al. (2016) and Dhyne, Petrin, Smeets, and Warzynski (2017) indicate firms operate in multiple product lines is a common case.

Regarding the literature about the firm competition in Turkey, there are not many studies that embodied the creative destruction paradigm. Nonetheless, as a recent study, Akcigit, Akgunduz, Cilasin, Ozcan-Tok, and Yilmaz (2020) tackled the slowdown in business dynamism issue through a similar model that we have here. Accordingly, the authors found out that Turkish economy started to show some slowdown signals for the business dynamism. Especially, the decreasing rate of

employment growth together with increasing market concentration is highly tied up with this thesis. As we will see, the low rates of employment growth for especially larger firms is a vital sign of market power accumulation. Moreover, as we will see, market concentration can highlight higher market power in some cases, and Akcigit et al. (2020) highlight the fact that current market concentration is a result of market power. On the other hand, this thesis supports this argument with the current condition of Turkish economy but extends it through a counterfactual analysis where a more efficient and competitive market structure can also be linked with the market concentration but a market concentration accompanied with the employment growth.

There are many studies that is focused on the business dynamism issues through using creative destruction paradigm. In Akcigit and Ates (2019) and Akcigit and Ates (2021), highlight some of the empirical regularities which point out the declining business dynamism in the U.S. economy, especially after the 1980s, and try to explain these facts by a declining rate of imitation by laggard firms. Some studies try to come up with a more comprehensive explanation like De Ridder (2021) where he points out the relation between the slowdown in business dynamism and the increasing usage of intangible capital (software etc.) in production.

Olmstead-Rumsey (2022) defines the innovative sector as a duopoly (competition through differentiated products) with heterogeneous patent qualities while tackling the productivity slowdown in the U.S. Another novel study, Bloom, Jones, Van Reenen, and Webb (2020) approaches economic growth from a different perspective and links the decrease in productivity with the difficulties of coming up with innovative ideas. On the other hand, Kroen, Liu, Mian, and Sufi (2021) and Liu, Mian, and Sufi (2022) approached some of the business dynamism related issues with the persistence of lower interest rates.

Alternatively, Peters and Walsh (2021) used a semi endogenous growth model to explain similar concerns regarding the slowdown in the U.S. business dynamism and found that decreasing population growth rates can explain such trends. Similarly, another demographic explanation comes from Karahan, Pugsley, and Sahin (2019)

where authors link the decline in the labor supply growth with the decline in the startup rates and so the business dynamism. The Schumpeterian type of models also tackles declining business dynamism and related observations. Aghion, Bergeaud, Boppart, Klenow, and Li (2022) points out the decline in innovative activities through the efficiency advantage of large firms where they have the ability to spread into new markets, which causes further concentration.

## CHAPTER 3

### MODEL

#### 3.1 Structure

The model starts with a simple household side, a common feature of the creative destruction models due to their focus on firm dynamics. Individuals have a logarithmic utility function with consumption as the sole argument. There is inelastic labor supply, and the consumption good is priced numeraire. There is no worker in the final good sector, workers devote their labor to the intermediate good sector (production worker or R&D worker), and the total labor supply is fixed to 1.

$$U = \int_{t=0}^{\infty} \exp(-\rho t) \ln C_t dt$$

Budget constraint of the households can be viewed as

$$C_t + \dot{A}_t = w_t L_t + r_t A_t$$

Each final good is produced in competitive markets and is later consumed by households. The final good which is a mixture of a variety of intermediate goods is produced through the production technology below

$$\ln Y_t = \int_0^1 \ln \left( \sum_{f \in S_{it}} y_{fit} \right) di$$

The final good producer uses the intermediate good  $i$  that it bought from the monopolist  $f$  at time  $t$ , which can be seen from the above production function, so there is a perfect substitution for a given product. On the other hand, monopolist behavior depends on the fact that different products are not substitutes; thus, in equilibrium, each production line has its monopolist as the sole producer of that line. We will analyze how monopolists emerge in this setting to make a coherent picture.

One crucial assumption of this class of models is the linear (in productivity and labor) production technology in the R&D sector. This assumption ensures that an increase in the productivity level will correspond to a proportional decrease in marginal costs. Due to Bertrand competition, the more productive firm will exploit its advantage in cost efficiency and capture the whole market by pricing the product to the marginal cost of the less productive firm, which also reflects the competitive nature of the intermediate good sector. One can also approach firms' problem through the Cournot competition, but it will not be desirable due to difficulties in analytical tractability. That is, under Cournot competition, firms who produce in their respective sectors should be determined manually in the data, which is not the case for Bertrand competition since it assumes that only the most productive firm produces in a sector. The linear production technology in the intermediate sector will follow the form

$$y_{fi} = q_{fi}l$$

where  $l$  stands for the labor and  $q_{fi}$  is the productivity level of firm  $f$  that operates in sector  $i$ .

Another advantage of linear production technology comes from the fact that quality ladders are a natural implication given that each productivity improvement occurs proportional to a common factor (step size) which is identical across all sectors and firms. If we define this innovation step size as  $\lambda$ , then if a firm with productivity level  $q_{it}$  makes an innovation between  $t+\Delta t$ , this will lead to a new productivity level of  $q_{i(t+\Delta t)} = \lambda q_{it}$ .

Since step size is independent of the firm characteristics, if we denote all the past innovations that a firm  $f$  undertake in the product line (market)  $i$  with  $n_{fit}$ , then we can write the relative productivity level of firms as follow

$$\frac{q_{fit}}{q_{-fit}} = \frac{\lambda^{n_{fit}}}{\lambda^{n_{-fit}}} = \lambda^{n_{fit}} - \lambda^{n_{-fit}} \equiv \lambda^{m_{fit}}$$

Basically, a firm's standing on the quality ladder depends on the number of innovations that it made. If a firm makes an innovation in a period, then it moves to one rung ahead in the quality ladder next period, and so on. Hence, the productivity difference or the technology gap can be defined through a simple statistic in the form of  $m_{fit}$ . Note that  $m_{fit}$  will be the most crucial statistic in this structure since we can sufficiently describe each firm's payoff with it. For the rest of the discussions, I will drop the firm subscript since we are interested in the product lines with a single producer. The productivity level of a given product line can be improved in three ways. The already active monopolist in the production line can make an improvement in productivity by making a further innovation which would also raise the profits of the firm that it gets from the markups. On the other hand, creative destruction will also positively affect productivity, which can be done either by an entrant or an incumbent. In the case of an entrant innovation, the productivity gap will reset to unity, that is, the entrant with superior technology would have a one step lead over the previous owner of the production line. Similarly, an incumbent that makes a successful innovation would also get a one step lead over the previous leader. Hence, the innovation dynamics affect markups in two different ways. In the case of an own innovation, the markups will increase on average. On the other hand, if the entrant or incumbent will come up with the innovation, the markups will decrease to the lower bound for an active market since the markup defining productivity gap would be unity.

At this point, how Peters (2020) contributes to Klette and Kortum (2004) needs a brief explanation. Firstly, one drawback of the first generation creative destruction models was that the Arrow replacement effect entirely dictates such models (Aghion and Howitt (1992)), that is, in the equilibrium of those models, only the entrants make innovations. In contrast, incumbents completely lose their incentive to innovate. Klette and Kortum (2004) changed this strong narrative by showing that in the equilibrium of their model, incumbents also innovate so that both incumbents and entrants maintain innovation incentives. However, the form of innovation in

Klette and Kortum (2004) only allows for horizontal innovations, so when an incumbent innovates, it randomly replaces a producer in a production line, so the competition dynamic still has a weak basis. On the other hand, Peters (2020) adds an own-innovation channel (in terms of vertical innovations) to Klette and Kortum (2004), so when an incumbent innovates it makes an improvement over a product that it has already been producing. This novel channel is of crucial importance, and the reason why incumbent firms undertake own innovation in the model of Peters (2020) is related to the markups. Previously, the Arrow replacement effect and appropriability effect create a strong negative incentive for the leader firms, but in Peters (2020), a firm can increase its markups by making own-innovations, so a clash between the old creative destruction and new markup increasing own-innovation channel become the decisive force of the firm dynamics in this new model.

Regarding some other details of the model, R&D expenditures of firms follow a modified convex cost function with respect to the arrival rate of innovation. Intuitively, as the quality of innovation increases, the marginal cost to produce such innovation will increase too. A supporting example can be given from Bloom et al. (2020) where authors point out that finding new ideas and so coming up with new innovations gets harder as technology advances. Hence, to come up with further innovations, more resources needed to be devoted. At the same time, in order to solve the value function in the dynamic equilibrium part and reach a unique solution, the cost function is needed to be convex in its arguments which is a fact that is generally exploited by the literature. In the context of Peters (2020), this convex cost function not only enables us to solve the dynamic problem but also generates a closed form solution for the value function which doubles its significance. The cost function takes the below form

$$\Gamma([x_i, I_i]; n, [m_i]) = \sum_{j=1}^n c(I_i, x_i; m_i), \quad \text{and} \quad c(I, x; m) = \lambda^{-m} \frac{1}{\varphi_i} I^\eta + \frac{1}{\varphi_x} x^\eta.$$

From the first term of the cost function, we can observe that as the technology gap increases between the leader and follower firms, the cost of undertaking an innovation becomes less costly for the leader. Moreover, the terms  $\varphi_I$  and  $\varphi_X$  summarize the associated costs of innovation processes. Moreover, the term  $\eta$  being bigger than 1 guarantee the required convexity of the cost function.

In order to understand the equilibrium dynamics of the model both static and dynamic allocations needed to be analyzed. In order to calibrate the model, the equilibrium conditions for the dynamic model will be provided under a set of assumptions. Then, the unique stationary equilibrium through solving the dynamic problem will be tackled by the derivations that are found in the static allocations part.

### 3.2 Static allocations

As previously mentioned in detail, due to Bertrand competition, the leader firm will use limit pricing, so the marginal cost of the follower firm would shape the leader firm's pricing strategy, let  $q_i$  denote the productivity level of the most productive firm, and  $q_{-i}$  stands as the productivity level of the follower firm (second most productive firm). Then, the equilibrium markup can be found as

$$\mu_i \equiv \frac{p_i}{mc_i} = \frac{p_i}{w/q_i} = \frac{w/q_{-i}}{w/q_i} = \frac{q_i}{q_{-i}}$$

The linkage between the quality levels and quality ladders will be exploited further in the dynamic equilibrium part. In this section, time subscripts are dropped in all steps since we are analyzing the static equilibrium that brings the optimum values of the final and intermediate good sectors. Demand for the intermediate good  $i$  follows a simple scheme that depends on the price that the monopolist set. Due to Cobb-Douglas specification, every sector ends up having the same amount of sales. Hence, demand for the intermediate good  $i$  can be written as

$$y_{it} = \frac{Y_t}{P_{it}}.$$

The price of the intermediate good  $i$  will be determined through the Bertrand competition. Since there is limit pricing, the firm with the higher productivity level will set the price of the product to the marginal cost of the competitor firm, which will discard the laggard firm since the follower firm can only have negative profits if it chooses to produce under this scheme.

$$p_{it} = \frac{w_t}{q_{-it}},$$

where the marginal cost of the more productive firm will be (due to linearity assumption)

$$mc_{it} = \frac{w_t}{q_{it}}.$$

It follows that only the more productive firms produce in their respective markets, which is the direct implication of the Bertrand competition and monopolistic nature of the intermediate good sector. Hence, less productive firms do not undertake any production.<sup>1</sup>

We can show that the optimum labor level for any intermediate good product, using  $q_i p_i = \mu_i w$  (firm subscript is dropped since results depend on the sole producer (monopolist) in a given product line which exactly corresponds to the most productive firm competing over that product)

$$l_i = \frac{y_i}{q_i} = \frac{Y}{q_i p_i} = \frac{Y}{\mu^i w}$$

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<sup>1</sup>In this model, two firms cannot have the same productivity level since any innovation will carry the innovation frontier further, so there is no possibility of being in neck-and-neck position, and firms make positive profits under every circumstance. On the other hand, in a similar context, Akcigit and Ates (2019) exploited the fact that firms can end up in neck-and-neck position after successful innovation by the follower, which boosts competition further.

In a similar fashion, we can write the profits of the monopolist in the intermediate sector ( $m_{it} \geq 0$ ) as a function of the technology gap and step size

$$\pi_i = (p_i - mc_i)y_i = \left(p_i - \frac{w}{q_i}\right)y_i = \left(\frac{p_i q_i - w}{q_i}\right)y_i = \left(\frac{w(\mu_i - 1)}{\mu_i w/p_i}\right)y_i$$

$$\pi_i = \left(1 - \frac{1}{\mu_i}\right)y_i p_i = \left(1 - \frac{1}{\mu_i}\right)Y$$

Now, we can shift the setting from the product level to the firm level. The above equations clarify the static outcomes for the product level. However, for the firm level results, we need to aggregate all products that the respective firm produces. Hence, if we denote the number of products that a firm produces by  $n_f$ . Given that the firm level markup is the average of the markups across all the products that a firm produce, that is,  $\mu_f = \left(\frac{1}{n_f} \sum_{i \in N_f} \frac{1}{\mu_i}\right)^{-1}$ . Then, the total employment at the firm level would

$$l_f = \sum_{i \in N_f} l_i = \sum_{i \in N_f} \frac{Y}{\mu_i w} = \frac{Y n_f}{w \mu_f}.$$

Employment at the firm level reveals an intuitive interpretation; a firm's employment motive is related to how many product lines it operates and how much markup it puts into its products. As the firm captures more product lines, the need for production labor increases. On the other hand, since a firm's value added would capture both the labor cost and markups, for a fixed level of value added, increasing the markups would correspond to a decrease that the firm devotes to the labor share. Hence, since the wage level is fixed in the equilibrium, employment would decrease under higher markups. This idea will also direct us to the misallocation channel for the labor share.

By aggregating all the firm level employment, we can reach the aggregate number of production workers in the economy.

$$L_{Pt} = \int_f l_{ft} df = \int_f \sum_{f \in N_f} \mu_{it}^{-1} df = \frac{Y_t}{w_t} \times \left( \int \mu^{-1} dG_t(\mu) \right)$$

In order to understand the misallocation related dynamics more apparent,  $dG_t(\mu)$  stands for the distribution of markups across all product lines for a given year (assuming that the time subscript  $t$  indicates year). Basically, since every product line is operated by a single producer, aggregating their individual level (also product level) markup decisions through relevant distribution will reflect aggregate markup dynamics of the economy for a given year which would be the most valuable and crucial statistic for this model.

Now, we can manipulate the above equation to reach the wedges that will be coming from the wage level in the economy; that is, if we leave the wage level alone for the above equation, then we get

$$w_t = \frac{Y_t}{L_{pt}} \times \exp\left(\int \mu^{-1} dG_t(\mu)\right) = Q_t \times \exp\left(\int \mu^{-1} dG_t(\mu)\right).$$

Note that  $Q_t$  captures the labor productivity, but the model also dictates the TFP through another channel. In order to see that we can

$$Y_t = L_{pt} \times w_t \times \left(\int \mu^{-1} dG_t(\mu)\right)^{-1} = L_{pt} \times Q_t \times \frac{\exp\left(\int \mu^{-1} dG_t(\mu)\right)}{\int \mu^{-1} dG_t(\mu)}$$

$$Y_t = Q_t M_t L_{pt}, \quad \text{and} \quad M_t \equiv \frac{\exp\left(\int \mu^{-1} dG_t(\mu)\right)}{\int \mu^{-1} dG_t(\mu)}$$

The above equations clearly show the cost of misallocation in the TFP by the wedge that is created through the markup distribution. The misallocation can be

clearly seen if we visualize the aggregate TFP by  $Q_t M_t$ . As long as there is no perfect competition, the market power will cause  $M_t$  to get a value lower than 1. On the other hand, the misallocation measure only equals 1 if there is perfect competition and no dispersion in markups. Hence, the markup dictating the behavior of firms that are coming from their market power would cause a misallocation in the form of reducing the aggregate TFP. Notice that the misallocation in TFP due to the markups channel is not related to the level of markups but rather to the dispersion. Hence, if there is no dispersion in markups and all firms (monopolists) increase their markups the same amount, then there would not be any effect on the misallocation. Misallocation in TFP is related to the fact that dispersion in markups would correspond that leaders of some product lines use their market power to increase their overall share at the cost of decreasing the productivity of the labor and the overall TFP of the economy.

The above equations also reflect the other misallocation source of the economy, which can be seen as the labor wedge. The labor share can be expressed via the distribution of the markups by

$$\frac{w_t L_{Pt}}{Y_t} = \Lambda_t, \quad \text{and} \quad \Lambda_t = \int \mu^{-1} dG_t(\mu).$$

Notably, the labor wedge depends directly on the level of markups. On the other hand, misallocation of the TFP depends on the dispersion of markups. Obviously, this result would be a crucial determinant of how markups would impact the aggregate economy. As we will see, due to the impact of level changes, labor share is more vulnerable to firms' markup decisions. In contrast, aggregate TFP seems to be more resilient to the changes in markups due to the fact that aggregate TFP would not be affected by the level changes but the dispersion. In contrast, dispersion changes relatively less compared to the level changes. Moreover, as we will soon observe in the dynamic setting, aggregate TFP is also strongly tied up with the creative destruction channel, which will indicate that to have a stronger impact of markups on the aggregate TFP, creative destruction needs to be weaker.

### 3.3 Dynamic setting

So far, all the misallocation related indicators that are generated within the model can be fully summarized by the marginal distribution of the markups. Hence, the static equilibrium provides the structure that links up the markups with the misallocation and market power. Next, we need another linkage to understand how firms' strategic decisions will shape the distribution of markups so that we can also express the markup distribution endogenously. To do so, we can use the structure that we already highlighted previously.

$$\mu_{it} = \frac{q_{it}}{q_{-it}} = \frac{\lambda^{n_{it}}}{\lambda^{n_{-it}}} = \lambda^{n_{it}} - \lambda^{n_{-it}} \equiv \lambda^{m_{it}}$$

Now, exploiting the quality ladder idea with a constant step size allow us to describe the equilibrium markups by the productivity gap. Regarding the linkage from firms' decision to markups, it is gradually become clear that one of the factors which firms would shape firms' behaviour would be the productivity gap. On the other hand, increasing the productivity gap to generate higher markups would not be the only factor that affect firm behaviour. To understand how the competition over product lines are occurring, we can examine how the productivity life cycle in those lines are evolved.

Briefly, there are three possible event that can change the productivity level of a product line. First two of them are directly following from the base paper of Klette and Kortum (2004), that is, creative destruction by an entrant or incumbent. Even though, these two events are different in nature, their effect on the productivity level is same. If a product line will be destructed by a firm (entrant or incumbent), then the productivity gap in that line would reset to unity. On the other hand, Peters (2020) introduced a novel channel to this structure in terms of an own-innovation channel which enables leader firms to open up the technology gap by further innovations which was not the case in Klette and Kortum (2004). The triggering motive is that markups are proportionally increase through the size of technology gap. Hence,

Peters (2020) the disincentivizing Arrow replacement effect is partially eliminated by the firms' desire to accumulate more market power and dictate higher markups.

As mentioned above, the technology gap is the unique statistic in determining the dynamics of the model, firms not only compete in the sector they are actively operating, but they can also extend to new product lines. Hence, value function captures both the expansion and creative destruction channels that is coming from the horizontal innovations. Moreover, firms can increase their value by own-innovation channel which enables them to exert market power. Under a set of assumptions, we can find closed form solutions for the underlying characteristics of the model.

$$\begin{aligned}
r_t V_t(n, [m_i]) - \underbrace{\dot{V}_t(n, [m_i])}_{\text{Capital Gain}} &= \sum_{j=1}^n \pi_t(m_j) - \sum_{j=1}^n \underbrace{\tau_t [V_t(n, [m_i]) - V_t(n-1, [m_i]_{i \neq j})]}_{\text{Creative Destruction}} \\
&+ \max_{[x_j, I_j]} \left\{ \sum_{j=1}^n \underbrace{I_j [V_t(n, [m_i]_{i \neq j}, m_j + 1) - V_t(n, [m_i])]}_{\text{Own-innovation}} \right. \\
&\left. \sum_{j=1}^n \underbrace{x_j [V_t(n+1, [m_i]_i, 1) - V_t(n, [m_i])]}_{\text{Expansion}} + \underbrace{\Gamma([x_i, I_i]; n, [m_i]) w_t}_{\text{Innovation costs}} \right\}.
\end{aligned}$$

The above value function is defined for the leader firm that is  $m$ -steps ahead of the follower firm. The idea behind the Hamilton-Jacobi-Bellman (HJB) equation is the standard no arbitrage condition that the firm's value cannot exceed or fall behind its expected return.  $r_t V_{mt}$  stands for the value of the firm discounted by the rate of return.  $\dot{V}_{mt}$  stands for the capital gains (appreciation or depreciation).

The first term on the right-hand side gives the total profits of the firm as a function of the technology gap. The second and third lines capture the innovation and expansion decisions of the firms together with the associated costs.

Note that the innovation costs are considered the costs associated with hiring research labor. Hence, the innovation cost function reflects the number of research workers that a firm has. In this regard, the rate at which a firm chooses to innovate or expand is divided by the respective efficiencies since the cost is lightened as the

efficiency increases. As highlighted before, due to the productivity advantage, as the productivity gap increases own-innovation becomes less costly for leader firms.

The last term on the first line stands for the value loss due to creative destruction, which occurs with the probability  $\tau_t$ . Note that this creative destruction term capture both the creative destruction by an incumbent,  $x$ , and by an entrant,  $z$ . Hence, we can think of the total creative destruction as

$$\tau = \int_{i=0}^1 x_{it} di + z_t.$$

Notably, the above aggregate creative destruction formula only holds for the case of free-entry. As usual, in order to satisfy the free-entry condition, we need to equalize the value of an entrance by a firm into the market to the value of not entering the market at all, which would be equal to 0. If the valuation would not hold with equality, then there would be an opportunity for either outsiders or insiders that such an arbitrage opportunity will break down the equilibrium dynamics. Remember that an entrant firm's entrance cost to a market would equal the efficiency level of wage it will pay to the labor. Hence, given the wage rate,  $w_t$  and the rate of entry efficiency (or the efficiency of entrant labor),  $\phi_z$ , the free-entry condition for a firm that would enter a market with a productivity gap of 1 would be

$$V_t(1, 1) \leq \frac{1}{\phi_z} w_t = 0, \quad \text{which holds with equality if } z > 0.$$

### 3.4 The stationary equilibrium

In this section, the stationary equilibrium of the model will be described. Firstly, the labor market condition must be satisfied that the total number of production workers and research workers must give the aggregate labor in the economy, and since labor is supplied inelastically, the aggregate labor would need to be 1.

$$1 = L_{Pt} + L_{Rt} = L_{Pt} + \frac{1}{\phi_z} z_t + \int_{i=0}^1 \left( \frac{1}{\phi_x} x_{it}^\eta + \lambda^{-m_i} \frac{1}{\phi_I} I_{it}^\eta \right) di.$$

Now, we can define the balanced-growth path which is also called the stationary equilibrium.

**Definition:** The balanced growth path of the economy is a tuple of prices and allocations  $\{w_t, r_t, p_{it}, l_{it}, I_{it}, x_{it}, z_t, y_{it}, c_t\}$  such that i) constant growth for aggregate variables, ii) household maximize utility through choosing the pair  $[y_{it}, c_t]$ , firm problem solves for the optimal bundle of  $[I_{it}, x_{it}, p_{it}]$ , iv) the market clearing and free-entry conditions hold, and v) the stationary distributions of markups and firm size exists.

Maybe the most catchy part of this model also lies in the last condition of the above definition. The model explains market power as the motivation to capture a higher share of overall profits. To do so, firms need to innovate in the production lines they already own. Hence, the own-innovation is tied up with market power. Even though the above scheme of interdependent relations seems complicated, the model allows us to reach the stationary equilibrium. This analytically tractable system provides solutions for the value function of the firms so that we can quantify their innovation and expansion strategies. The below proposition algebraically summarizes the above discussion.

**PROPOSITION 1:** Given that discount rate satisfies  $\rho > \frac{\eta-1}{\eta} \left( \frac{1}{\eta} \frac{\varphi_x}{\varphi_z} \right)^{1/(\eta-1)}$ , the balanced-growth path of the economy can be explained by the below system

i . The value function can be written in an additively separable form such that

$$V_t(n, [m_i]) = \sum_{i=1}^n V_t(m_i) = V_t^P n + \sum_{i=1}^n V_t^M(m_i), \quad \text{with}$$

$$V_t^P = \left( \pi_t(1) + (\eta-1) \frac{x_t^\eta}{\varphi_x} w_t \right) \frac{1}{\rho+\tau}, \quad \text{and} \quad V_t^M(m) = \left( \pi_t(m) - \pi_t(1) + (\eta-1) \lambda^{-m} \frac{l_t^\eta}{\varphi_l} w_t \right) \frac{1}{\rho+\tau}.$$

- ii . The optimum allocation, which stems from the firms' problem, provides the set of time-invariant solutions in the form of  $(I, x, z, \tau)$ . Moreover, innovation and expansion rates have below closed-form solutions

$$I = \left( \frac{\lambda - 1}{\lambda} \frac{1}{\rho + \tau} \left( \frac{\varphi_I}{\eta} \frac{Y_t}{w_t} - \frac{\eta - 1}{\eta} I \eta \right) \right)^{\frac{1}{\eta - 1}} \quad \text{and} \quad x = \left( \varphi_x / \varphi_z \eta \right)^{\frac{1}{\eta - 1}}$$

- iii . The unique markup distribution is stationary and the misallocation measures of  $M$  and  $\Lambda$  are constant.
- iv . The economy wide growth rate is same for all variables that in the equilibrium the growth rate can be found as

$$g = \dot{Q}_t / Q_t = \ln \lambda \times (I + x + z) = \ln \lambda \times (I + \tau).$$

The additive functional form for the value function is very useful to highlight the contribution of Peters (2020) to Klette and Kortum (2004). The first term,  $V_t^P$ , is closely tied up with the approach of Klette and Kortum (2004). It captures the value of producing a product with one step productivity advantage over the follower firm, which can be considered as expansion or creative destruction by an incumbent. As in Klette and Kortum (2004), this expansion technology allows firms to linearly scale their value (ability to produce innovations that generate the same value independent from the product line) over all the product lines.<sup>2</sup>

On the other hand, the second term of the value function,  $V_t^M$ , highlights the originality of the model of Peters (2020). It represents the value from subsequential innovations a firm makes in an existing line of its' own. Hence, it also symbolizes the market power and markup linkage implicitly. To gain more market power, a firm needs to invest in own-innovation and widen the quality gap so that it can increase the

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<sup>2</sup>Recent literature Akcigit and Kerr (2018) tackled the idea of linear scaling of expansion technology (external innovations in Akcigit and Kerr (2018)), which simplifies the model significantly in this case.

markups. Furthermore, we also see that the creative destruction parameter entered the value function in a similar form to the discount rate. As creative destruction becomes more prominent, the value of gaining market power becomes less attractive since the risk of losing the whole production line instantaneously also increases. Hence, the discount and creative destruction rates balance the market power ambition of the firms.

### 3.5 The distribution of markups

In this section, the emergence of the unique distribution of markups will be analyzed. To construct the distribution, we need a set of differential equations that would dictate the behavior of markups. Hence, the previously mentioned relation between the quality gap and markups becomes handy. Since a single statistic can fully explain markups for a given product, a leader firm's productivity advantage over the follower firm in that line, the distribution of markups can be solely characterized by the quality gap for each product line in the economy. Thus, the below differential equations would be the path to the markups distribution

$$\dot{v}_t(m) = \begin{cases} -(\tau + I)v_t(m) + Iv_t(m-1) & \text{if } m \geq 2 \\ \tau(1 - v_t(1)) - Iv_t(1) & \text{if } m = 1. \end{cases}$$

It can be seen by the above equations that to donate the set of products with different quality gaps, we need to understand how firms can leave and enter that state. Firstly, for the set of products with a unit quality gap, if an own-innovation happens in a product with a unity gap, then the product will enter the next state (e.g., a quality gap of two). On the other hand, if creative destruction (either by an incumbent or entrant) occurs in a product line, it will reset the productivity gap (the product independent from the quality gap enters the state of a unit quality gap), except for the case where the quality gap is already unity. Similarly, if a product is in the state of two or more quality gap (let us say  $\bar{m}$ ), then any own-innovation or creative

destruction in that product line cause the product to leave its previous state. On the other hand, if an own-innovation occurs in a product line with a quality gap of  $\bar{m}-1$ , then that product becomes a member of products with a quality gap  $\bar{m}$ .

Before defining the distribution of markups, it is worth noting that both growth rate and the distribution of markups are shaped by the endogenous forces of the model, namely, own-innovation and creative destruction ( $I, \tau$ ). The growth rate is positively related to both  $I$  and  $\tau$ , whereas markup distribution is not. As highlighted before, own-innovation channel increases the markups, but creative destruction via expanding or entering reduces markups to the lowest possible value. Hence, the nested relation of own-innovation, creative destruction, and growth also determines markups. In the later parts of the paper, we will see how this model explains the complex dynamics of the Turkish economy with these forces. Now, we can make the formal definition for the distribution of markups and related misallocation dynamics.

**PROPOSITION 2:** Given that the model reaches the stationary equilibrium, let the equilibrium values of creative destruction and own-innovation be  $\tau$  and  $I$ . Suppose

$$\vartheta = \frac{\ln(1 + \vartheta)}{\ln \lambda}, \text{ and } \vartheta = \frac{\tau}{I}$$

i . The unique stationary markups distribution follows the below form

$$G(\mu) = 1 - \mu^{-\vartheta}$$

ii . The misallocation indexes of  $M$  and  $\Lambda$  can be summarized as

$$M = e^{-1/\vartheta} \frac{1 + \vartheta}{\vartheta}, \text{ and } \Lambda = \frac{\vartheta}{1 + \vartheta}$$

The above proposition highlights the main theoretical contribution Peters (2020) with the explicit linkage of markup distribution with the ratio of creative destruction to own-innovation. This term is named churning intensity by the author and resembles a business dynamism gauge. As the churning increases, more firms enter the market, and more firms expand to new markets. In contrast, a decreasing churning would indicate relatively more own-innovation, that is, firms with higher market power and a less dynamic market. Moreover, the markups have a unique Pareto distribution at the equilibrium, and the shape parameter of this Pareto distribution is the model generated churning intensity. Hence, the distribution of markups is shaped endogenously by this statistic. The intuition follows the above description; as the churning intensity increases, the distribution would have a thinner tail that will indicate a lower average markup with less variation in markups. On the other hand, as the churning intensity decreases, firms can accumulate more market power and increase the overall markups with a lesser threat of destruction so that the average markups will increase.

Regarding the misallocation measures, the model also gives closed-form solutions for both measures, and they only depend on the churning intensity, so the own-innovation and creative destruction. Similar to the above results, a higher churning intensity reduces the monopoly power and brings a more competitive market. Misallocation also decreases, which corresponds to a higher TFP and labor share.

Next, the model allows us to explicitly formulate the average markups at the product and firm levels. It is essential to distinguish this because we will apply the latter while calibrating the model. Furthermore, it is crucial to understand how both mechanisms work. Firstly, if we assume that a firm produces a product for eternity, then we can write down the logarithm of average markups as a function of product age as following

$$E[\ln \mu | \text{product age} = a_p] = \ln \lambda(1 + I a_p).$$

In this case, the model explains an increase in the average logarithm of markups proportional to own-innovation, which also increases with the product age, which corresponds to the firm age in this case since there is no expansion or creative destruction in this specification. Note that, as the own-innovation rate increases for a given step size, the firm accumulates more market power which can be seen from the higher average markups that it can dictate.

However, it is also clear that the above relation cannot result in a Pareto distribution for markups. On top of it, the immortal firm assumption is quite suspicious. Hence, markup dynamics should depend on factors other than own-innovation at the firm level. Unsurprisingly, the force that comes into play would be creative destruction which can randomly result in a firm's expansion by using it or losing a production line by being exposed to it. Therefore, average markups at the firm level would depend on a more complex equation. Before going into the details, I will describe the analytical relation of how the average markups are determined at the firm level.

$$E[\ln \mu | \text{firm age} = a_f] = \ln \lambda(1 + I \times E[a_p | a_f]), \quad \text{with}$$

$$E[a_p | a_f] = \frac{1}{x} \left( \frac{\frac{1}{\tau} (1 - e^{-\tau a_f})}{\frac{1}{x+\tau} (1 - e^{-(x+\tau)a_f})} - 1 \right) (1 - \varphi(a_f)) + a_f \varphi(a_f), \quad \text{and}$$

$$\varphi(a) = e^{-xa} \frac{1}{\gamma(a)} \ln \left( \frac{1}{1 - \gamma(a)} \right) \quad \text{and} \quad \gamma(a) = \frac{x(1 - e^{-(\tau-x)a})}{\tau - x \times e^{-(\tau-x)a}}$$

Hence, if both arguments are increasing, then the model implies both channel exists, but the dominating markups will give extra strength to own-innovation

efficiency. Since the productivity growth is proportional to own-innovation and creative destruction, it is calculated interdependently with the own-innovation and creative destruction rates. Simply, a higher value of  $I$  (own-innovation) will cause a higher value of  $g$ .

Regarding the employment dynamics of the model, given the equilibrium values, we can find closed-form solutions for both the size of the active firms and the fraction of the sales that are coming from the firms that produce  $n$  or fewer products, below given the equations for both characteristics in respective order.

$$F = \frac{1 - \frac{x}{\tau}}{\frac{x}{\tau}} \ln \left( \frac{1}{1 - \frac{x}{\tau}} \right)$$

$$\Omega_n = 1 - \left( \frac{x}{\tau} \right)^n$$

Since  $x$  represents the expansion efficiency and part of the creative destruction that is coming from incumbent firms, the above equations indicate that a higher expansion efficiency would indicate a relatively less number of firms. Nevertheless, the size of those firms would be larger. Hence, we can also interpret a higher expansion efficiency as a linkage to the higher market concentration. This result will be pretty essential in our counterfactual analysis part.

An increase in employment of firm size is strongly related to the expansion rate of a firm, especially the relative importance of expansion to the own-innovation. The firm size increases as the firms' primary motivation shifts to expansion rather than own-innovation. Note that the firm size can be explained by the below relation

$$\underbrace{E[\ln l_f | a_f] - E[\ln l_f | 0]}_{\text{Life-cycle of employment growth}} = \underbrace{(1 - \gamma(a)) \sum_{j=1}^{\infty} \ln j \times \gamma(a)^{j-1}}_{\text{Sales growth}} - \underbrace{\ln \lambda (I \times E[a_p | a_f])}_{\text{Markup growth}}$$

At one extreme, Klette and Kortum (2004) used the argument of proportional expansion and employment. Since their model does not include an own-innovation channel, any expansion would result in a proportional increase in employment. However, the existence of own-innovation disturbs this one-to-one relationship. Moreover, in another extreme, in a model where own-innovation is the sole purpose of firms with no expansion, there would not be any relation between the age of the firms and sales. Since Peters (2020) claims the existence of both channels, I used the regression below to show that extreme cases are not a realistic scenario, and net sales are affected by firm size and firm age.

Table 1. Net Sales and Employment Relation (All Sample)

| Dependent Variable: Log Net Sales |                       |
|-----------------------------------|-----------------------|
| Cohort Age                        | 0.1092***<br>(0.0009) |
| Log Labor                         | 0.8169***<br>(0.0019) |
| Time Fixed Effects                | ✓                     |
| Industry Fixed Effects            | ✓                     |
| N                                 | 1471418               |
| R <sup>2</sup>                    | 0.3513                |

Standard errors in parentheses, errors are clustered at the firm level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## CHAPTER 4

### QUANTITATIVE ANALYSIS

#### 4.1 The data

Firstly, all the data used in this study comes from the Entrepreneurship Information System (EIS), created by the Ministry of Industry and Technology. This database consists of data sets that is gathered from 8 different institutions. However, for the sake of this study, only the Firm Registry Data, Social Security Data, and Balance Sheet Data are used. Access to this data source is limited, and researchers can only study in a private area inside the ministry, which is also provided by the ministry. Moreover, there are strict limitations on data usage, both in terms of the data size and privacy of the information. Recently, this data has been started to be used in various studies such as Akcigit et al. (2020) and Ozlale and Polat (2019).

A brief explanation regarding how the data sources are used would be as follows: Firm Registry Data is used to gather information on sector classification (NACE Rev. 2), firms' market entrance dates, and determining cohort ages. Social Security Data is used to access the data on employment and labor costs. Lastly, Balance Sheet Data is employed to estimate the material costs, markups and value added. The starting date for most of the data in the Entrepreneurship Information System is 2006. To have a similar timeline to Peters (2020), and also due to worries regarding the significant increase in the minimum wage in 2016 (a possible increase in informal labor), which is implied by Akcigit et al. (2020), the data for the period 2006-2016 is used in this study.

In order to estimate the markups, I follow the strategy of Akcigit et al. (2020), who also used the same data set in their study. The authors found the markups by subtracting the total labor and material costs from the sales. However, to do that they initially need to estimate material costs because Turkish Balance Sheet data does not include firms' material costs. Hence, they estimate the material cost by taking the difference between the cost of sales from labor costs.

Some more details regarding the data will be provided in the calibration part. However, let us start with some reduced form evidence on the life cycle of markups. The predecessor paper of Klette and Kortum (2004) depends on the fact that firms grow only horizontally, so it ignores the own-innovation channel in Peters (2020). However, suppose firms only grow horizontally in a random way. In that case, there should not be a systematic relation between cohort age and markups since this model requires firms to make own-innovation to affect the markups. Hence, before analyzing the results through the lens of Peters (2020), we need some evidence on the existence of own-innovation channel, which can be observed if there is a positive relation between the cohort age and markups.

#### 4.2 Life-cycle of markups and empirical findings

In the previous section, we saw that the theory implies an increasing relation between log markups and cohort age at the firm level. To be precise, log markups and cohort age indicate a non-monotone relation that will start to decline after some age and converges to a limit value which is also closely related to churning intensity. However, the theory indicates a decrease in markups not before a firm reach to age of 10. In our sample, the maximum cohort age is 9, and it actually corresponds to a 10-year-old firm (since the entrants are considered as age 0). Therefore, we expect to see a clearly increasing relation between cohort age and log markups in our sample.

Note that only firms who are active in the market are used in the regressions and later the calibration part; to do that, I ignore the firms who do not report any hired workers. Due to the data construction, I made this specification over the December of each year. Similarly, to eliminate any errors that would be due to the data itself, I only consider the firms with positive material costs. This specification also allows me to have the same observation number for each group I analyzed. Regarding the groups, I first did the analysis for the whole sample. Then, I repeat the exercise for the firms with 20+ and 50+ workers separately. In the case of 50+ workers, the sample is constructed by the size and scale classification of the recently updated

SMEs (small and medium-sized enterprises). Hence, not only does the sample have firms with 50+ workers, but it also restricts the firms in the sample to have at least one item of their financial statement exceeding 250 Million Turkish Lira.

Lastly, I also focused on the markup and cohort age relation in terms of the technology level classification. According to this classification, there are four technology groups, namely, low, mid-low, mid-high, and high. The first two groups include relatively more firms than the last two groups, which is not surprising when we consider the structure of the manufacturing sector in Turkey. In a separate specification, I only took the firms that are in the technology group of medium-high and high. Even though the sample size is relatively small, this specification carries a significant role. Intuitively, since our model is an innovation-based model of creative destruction, it can be argued that the most objective results regarding the model should have appeared in this specification; that is, either type of innovation, vertical or horizontal, are expected to be mostly made by the firms in these two groups.

To begin with, I will share the life-cycle of markups in Turkey for different groups as specified above. As mentioned previously, only firms which hire at least one worker and incur positive material costs included in the samples. While calculating markups for different cohort ages, I go in line with both Akcigit et al. (2020) and Peters (2020), and measure the markups within the industry groups that are defined by NACE Rev. 2. Then, the log markups of entering cohort is normalized to 0 and entrants are considered as age 0. One advantage of this specification is that we can directly observe the growth by comparing different cohort ages with entrants. Growth in markups and employment will also be quite crucial as a moment in the calibration part. I will start with the all sample specification and then give the details of 50+ firms and technologically advanced groups of firms. Almost in all parts, this ordering will be followed. Regarding the figures, the purple dots imply the size of the cohort. As expected, it is declining in age due to attrition. Moreover, confidence intervals around the values are for the 95% level.

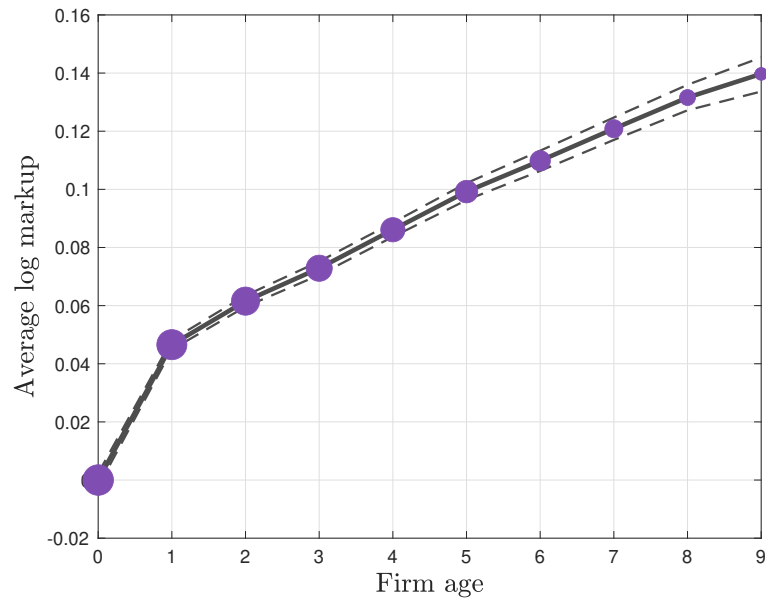


Figure 1. The life-cycle of markups for the all firms

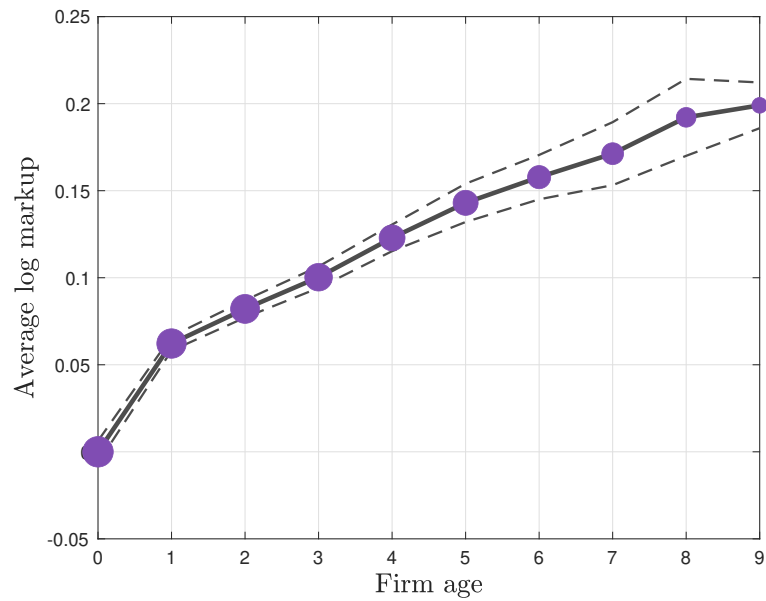


Figure 2. The life-cycle of markups for the firms with 50+ workers

All of the markup life-cycle figures clearly show the increasing nature of markups as the firms get older. Accordingly, if we consider the whole sample, 7-year-old firms increase the markups on average %12 more than the entrants. However, when we consider the firms with 50+ workers, the growth of the markups for the 7-year-old firms on average becomes %17.

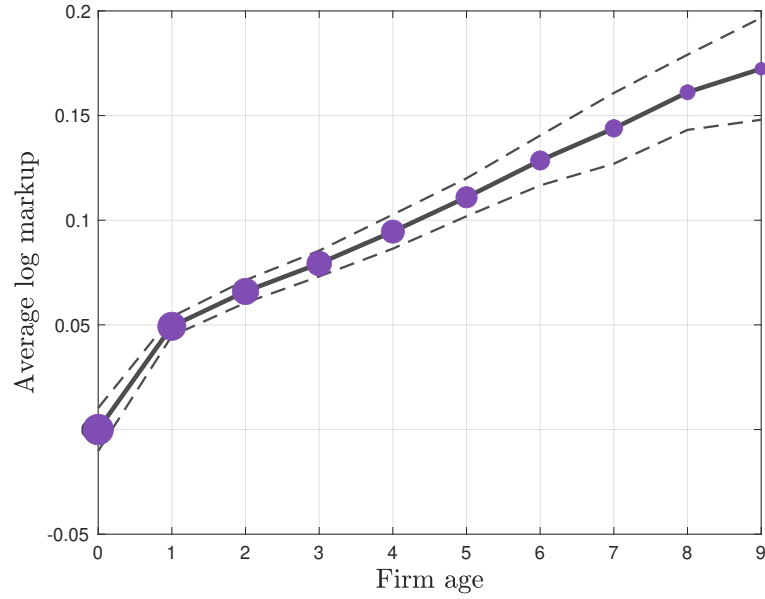


Figure 3. The life-cycle of markups for the high tech firms

Lastly, for the relatively high technology firms, the markup growth for 7 year-old-firms on average equals %14. Here, we can point out one difference with the Peters (2020) where the author finds a concave life-cycle markup for the Indonesian firms with 20+ workers, which starts to decline after the age of 7. However, in our case, all specifications show an apparent markup increase for all ages. Only, for the sample with 50+ workers, we see a relatively small markup growth after the 8. Hence, if we had a longer time horizon, we might observe a similar concave pattern too. Another remarkable point is that the higher markup growth for firms bigger in size seems to be a valid point since 50+ firms on average has %5 higher markup growth when compared to all sample and %3 higher markup growth when compared to technologically advanced firms.

Now, we can focus on the empirical evidence regarding the markup and age relation. Importantly, in all regressions, time and industry fixed effects are added as controls, and standard errors are clustered at the firm level. Before analyzing the results individually, we can see the clear impact of adding the control set of log labor and log material on the impact of cohort age through a decreasing effect on the log markup in all specifications with an increasing value of  $R^2$ . Below are some of the results in line with the above arguments.

Table 2. The Life-Cycle of Markups in Turkey (All)

| Dependent Variable: Log Markup | (1)                   | (2)                   | (3)                   |
|--------------------------------|-----------------------|-----------------------|-----------------------|
| Cohort Age                     | 0.0548***<br>(0.0011) | 0.0306***<br>(0.0008) | 0.0242***<br>(0.0007) |
| Time Fixed Effects             | ✓                     | ✓                     | ✓                     |
| Industry Fixed Effects         | ✓                     | ✓                     | ✓                     |
| Log Labor                      |                       | ✓                     | ✓                     |
| Log Material                   |                       |                       | ✓                     |
| N                              | 943576                | 943576                | 943576                |
| R <sup>2</sup>                 | 0.1160                | 0.3926                | 0.5368                |

Standard errors in parentheses, errors are clustered at the firm level.

The panel is unbalanced, but only firms with positive material cost and labor are added.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Above, we see the regression results for the whole sample, which is built on the previous description. The sample size is close to 1 million observations. After adding all the controls, the cohort age still has a highly significant impact on the log markup, which is close to 0.025 log points. On the other hand, there are still many factors that we probably omitted, so for now, it would be better to compare the results with each other rather than comparing them with Peters (2020), even though the specifications are not so different.

Next, we can check the classification using the updated SME's definition which is already mentioned. One might consider this specification the closest to "the superstar firms" argument, which is used to describe the firms with the highest market power by the literature. Nonetheless, compared with other specifications, even after adding all the controls, the effect of cohort age on log markups is above 0.03 log points. This is almost three times higher than the values that Peters (2020) found in his study. Note that adding log labor as the single control as in the second specification only reduced the effect of cohort age by around 0.05%. In contrast, log labor captured a significantly higher variation in log markup in other specifications.

Table 3. The Life-Cycle of Markups in Turkey (50+)

| Dependent Variable: Log Markup | (1)                    | (2)                   | (3)                   |
|--------------------------------|------------------------|-----------------------|-----------------------|
| Cohort Age                     | 0.06366***<br>(0.0040) | 0.0575***<br>(0.0035) | 0.0305***<br>(0.0028) |
| Time Fixed Effects             | ✓                      | ✓                     | ✓                     |
| Industry Fixed Effects         | ✓                      | ✓                     | ✓                     |
| Log Labor                      |                        | ✓                     | ✓                     |
| Log Material                   |                        |                       | ✓                     |
| N                              | 55826                  | 55826                 | 55826                 |
| R <sup>2</sup>                 | 0.3793                 | 0.4549                | 0.6314                |

Standard errors in parentheses, errors are clustered at the firm level.

The panel is unbalanced, but only firms with positive material cost and labor are added.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Actually, this might not be surprising because, as we will see in the calibration part, employment growth for larger firms is strictly lower than the other specifications. However, we should approach this relation cautiously since we did not add capital stock to our regressions, which might be the source of significant variation for the huge firms. In the original study, Peters (2020) did a similar analysis in Indonesia for firms in the manufacturing sector with 20+ employees. When he added the capital-labor ratio as an extra control, he found a decreased effect of cohort age of around 0.3%.

On top of it, as highlighted by Acemoglu and Ucer (2015), there might be some other structural explanations that affect growth in Turkey, such as institutional, bureaucratic, or political factors, which might, in turn, also affect firms' market power. Hence, we might need a different control set for this group to observe a less biased estimate of cohort age on the log markup. Briefly, the observed value probably captures some positive bias from factors that affect bigger firms more than relatively small ones.

Table 4. The Life-Cycle of Markups in Turkey (High Tech)

| Dependent Variable: Log Markup | (1)                   | (2)                   | (3)                    |
|--------------------------------|-----------------------|-----------------------|------------------------|
| Cohort Age                     | 0.0684***<br>(0.0058) | 0.0284***<br>(0.0036) | 0.0185***<br>(0.00306) |
| Time Fixed Effects             | ✓                     | ✓                     | ✓                      |
| Industry Fixed Effects         | ✓                     | ✓                     | ✓                      |
| Log Labor                      |                       | ✓                     | ✓                      |
| Log Material                   |                       |                       | ✓                      |
| N                              | 40373                 | 40373                 | 40373                  |
| R <sup>2</sup>                 | 0.1068                | 0.5277                | 0.6569                 |

Standard errors in parentheses, errors are clustered at the firm level.

The panel is unbalanced, but only firms with positive material cost and labor are added.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

The above table summarizes the effect of cohort age on log markups for the technologically advanced group of firms. As mentioned previously, this classification divides firms into low to high technology level groups. In order to analyze the group of firms that are more likely to innovate, I picked up the firms with the technology level of mid-high and high. The results for this group of firms are pretty interesting. First of all, the usual pattern of an increasing  $R^2$  value and decreasing coefficient by adding controls can be observed here too. Nevertheless, the coefficient of cohort age in the final specification is striking; it is lower than all the other specifications, especially the difference between this group and the group with 50+ workers is almost 0.012 log points which is surprisingly high. This difference can also be interpreted as such the firms with 50+ workers increase their markups on average %1.2 more than the firms with relatively high technology per year. Moreover, this value is the closest value to what Peters (2020) has found in his regression analysis of the Indonesian economy. To be more precise, Peters (2020) has found an impact between 0.010 and 0.014 for the effect of cohort age on the log markups.

Interestingly, we might also be observing an implicit linkage to a crucial theoretical assumption that is commonly adopted in the creative destruction

paradigm, the simple production technology which only depends on labor and productivity as inputs. The results found for the high technology firms can be interpreted as follows: Labor and material costs absorb the impact of log markups without adding capital as control which highlights the relatively less importance of capital for the sectors with relatively advanced technology. Simply, the innovative sector might be less capital intensive, as the theory suggests.

By no means having a value closer to Peters (2020) is a desirable property. However, to reflect a more competitive market environment, a lower impact of age on markups might carry some significant value since it also reflects how much market power firms can accumulate over time and the strength of creative destruction, etc. However, if we will make a comparison with the other specifications for the given set of controls, a more competitive market environment can be observed for the relatively high technology group. From the lens of the theory, the smaller effect of cohort age can be linked to less own-innovation or more creative destruction. However, the theory implies that markups are a distorting factor in the economy through misallocation created over the TFP and labor share. Therefore, I found it quite intriguing to do an exercise in the form of comparing the firms with a relatively high technology level to the ones with relatively bigger in size through calibration. This is precisely one of the motives of the next section.

#### 4.3 Calibration

To calibrate the model, we need four aggregate moments: markup life-cycle, employment life-cycle, aggregate productivity growth, and firm entry rate. These four moments are sufficient to identify the four parameters which will fully dictate the model. Markup and employment life-cycle are defined in the same way as Peters (2020), that is, the average markup and employment growth of a 7-year-old firm. To do that, the log difference of the markups for 7-year-old firms and entrants is taken. One weak side of the above argument is related to the attrition and sample size difference between those two groups. However, since I try to replicate the model of

Peters (2020) for the Turkish economy, I try to align with his modeling strategy throughout the thesis as much as possible.

On the other hand, I used external sources to specify the aggregate productivity growth and firm entry rate. Regarding aggregate productivity growth, the Balance Sheet Data requires too much manipulation to reach a reliable estimate. Moreover, since the Balance Sheet Data does not include the informal sector, the productivity values might be misleading. Therefore, I used OECD data for the labor productivity levels to determine Turkey's aggregate productivity growth. OECD defined labor productivity in two ways: GDP per hour worked and GDP per person employed. Since the latter is the more relevant indicator for this study, I used the GDP per person employed definition of productivity while determining the aggregate productivity growth. Accordingly, the average aggregate productivity growth for the Turkish economy is found as 5%, whereas the corresponding value in Peters (2020) for the Indonesian economy was 3%. Next, the firm entry rate is taken from (Ozlale and Polat (2019)), which corresponds to 9.6%. The reason to refer to this study is that it mainly focuses on job creation dynamics, which makes it a reliable source. At the same time, my calculations of the entry rate also result in a similar value to what they have found. The discount rate is taken as 0.05, which is also what Peters (2020) used, and the cost function's curvature parameter is taken from Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018) as 2. Note that the mapping from the data to the model does not depend on the values of discount rate and curvature parameter.

Table 5. Moments and Structural Parameters (All)

| Targets           | Data   | Model  | Calibrated Parameters |                 |       | Outcomes |       |
|-------------------|--------|--------|-----------------------|-----------------|-------|----------|-------|
| Markup life-cycle | 0.1209 | 0.1209 | $\varphi_I$           | Innovative eff. | 1.781 | I        | 0.305 |
| Emp. life-cycle   | 0.4187 | 0.4187 | $\varphi_x$           | Expansion eff.  | 0.456 | x        | 0.188 |
| Entry rate        | 0.096  | 0.096  | $\varphi_z$           | Entry eff.      | 1.214 | z        | 0.031 |
| Agg. prod. growth | 0.05   | 0.05   | $\lambda$             | Step size       | 1.100 | $\tau$   | 0.219 |
|                   |        |        | $\eta$                | Cost function   | 2     |          |       |
|                   |        |        | $\rho$                | Discount rate   | 0.05  |          |       |

The table gives the outcomes and calibrated parameters for the sample with all firms. Markup life-cycle and employment-life cycle give aggregate growth of respective variables for 7-old-firms. Aggregate productivity growth is measured through the OECD statistics on labor productivity, and the entry rate is taken from the study of Ozlale and Polat (2019). All the parameters determined endogenously except for the cost function (taken from Acemoglu et al. (2018)) and the discount rate.

Table 6. Moments and Structural Parameters (High Tech)

| Targets           | Data   | Model  | Calibrated Parameters |                 |       | Outcomes |       |
|-------------------|--------|--------|-----------------------|-----------------|-------|----------|-------|
| Markup life-cycle | 0.1439 | 0.1439 | $\varphi_I$           | Innovative eff. | 32.58 | I        | 1.426 |
| Emp. life-cycle   | 0.5396 | 0.5396 | $\varphi_x$           | Expansion eff.  | 1.103 | x        | 0.254 |
| Entry rate        | 0.096  | 0.096  | $\varphi_z$           | Entry eff.      | 2.165 | z        | 0.019 |
| Agg. prod. growth | 0.05   | 0.05   | $\lambda$             | Step size       | 1.029 | $\tau$   | 0.274 |
|                   |        |        | $\eta$                | Cost function   | 2     |          |       |
|                   |        |        | $\rho$                | Discount rate   | 0.05  |          |       |

The table gives the outcomes and calibrated parameters for the sample with technologically advanced firms. Markups life-cycle and employment life-cycle give aggregate growth of respective variables for 7-old-firms. Aggregate productivity growth is measured through the OECD statistics on labor productivity, and the entry rate is taken from the study of Ozlale and Polat (2019). All the parameters determined endogenously except for the cost function (taken from Acemoglu et al. (2018)) and the discount rate.

Table 7. Moments and Structural Parameters (50+)

| Targets           | Data   | Model  | Calibrated Parameters |                 |        |        | Outcomes |  |
|-------------------|--------|--------|-----------------------|-----------------|--------|--------|----------|--|
| Markup life-cycle | 0.1713 | 0.1713 | $\varphi_I$           | Innovative eff. | 0.797  | I      | 0.2474   |  |
| Emp. life-cycle   | 0.1080 | 0.1080 | $\varphi_x$           | Expansion eff.  | 0.1359 | x      | 0.088    |  |
| Entry rate        | 0.096  | 0.096  | $\varphi_z$           | Entry eff.      | 0.767  | z      | 0.05     |  |
| Agg. prod. growth | 0.05   | 0.05   | $\lambda$             | Step size       | 1.135  | $\tau$ | 0.147    |  |
|                   |        |        | $\eta$                | Cost function   | 2      |        |          |  |
|                   |        |        | $\rho$                | Discount rate   | 0.05   |        |          |  |

The table gives the outcomes and calibrated parameters for the sample with the firms that have 50+ workers. Markups life-cycle and employment life-cycle give aggregate growth of respective variables for 7-old-firms. Aggregate productivity growth is measured through the OECD statistics on labor productivity, and the entry rate is taken from the study of Ozlale and Polat (2019). All the parameters determined endogenously except for the cost function (taken from Acemoglu et al. (2018)) and the discount rate.

If we make a comparison of outcomes and calibrated parameters for the three specifications, we can see some significant differences. First of all, the markup life-cycle values are higher for the samples with high tech firms and 50+ firms. Especially the sample with 50+ firms have a significantly high markup growth, but with the smallest growth for the employment is worrisome. On the other hand, high tech group has the highest employment life-cycle moment. When we look at the outcomes and calibrated parameters, there is a striking difference between the sample with 50+ firms and the rest of the specifications. The sample with larger firms has the lowest efficiency values for all channels, whereas the high tech sample has the highest ones in magnitude. However, remember that model indicates a clashing effect between innovation and expansion, so what we will later observe is that the sample with all firms and high tech firms will imply similar results. The reason would be related to the fact that even though high tech sample has very high values for all the efficiency parameters inside the model, implied results would be proportional due to their non-linear relationship to the aggregate outcomes.

As highlighted before, the difference in the effect of the age between the moments and the regression results might be related with the control set. Simply, there is less variation in log labor for the firms with 50+ workers, whereas there is a significant change for the high tech firms. Hence, in the empirical findings part, we probably observe that some variation in log markup is successfully captured by the log labor for the high tech firms so that the coefficient of the cohort age in that regression is reduced significantly. However, for the firms with 50+ workers, since there is no upward trend or variation in log markups, adding it as a control did not change the coefficient significantly as it was in the high tech setup. Actually, when we observe the regressions, we can see that too. Adding log labor to the 50+ worker firms specification reduces the coefficient of 0.006 log unit. On the other hand, adding log labor to high tech firm specification decreases the impact of cohort age by 0.04 log units. Adding capital stock to the regressions for the bigger firms might handle some of the bias, but since the model does not include capital as an input, I did not add capital stock as control which can be done as a robustness check later. As a remainder, Peters (2020) also did not use capital as a control for the markups measure; however, he showed that on average adding capital to labor ratio decreases the impact of cohort age on markups by around 0.35% per year. At the same time, Peters (2020) mentioned the fact that as firms get older and bigger they shift their input share from labor to material which can be related with the fact that controlling for material have the highest impact for the group with bigger firms.

Table 8. Sensitivity Matrix (All Firms)

|                                       | 5% Change in... |          |          |           | Initial Level |
|---------------------------------------|-----------------|----------|----------|-----------|---------------|
|                                       | $\tau_I$        | $\tau_x$ | $\tau_z$ | $\lambda$ |               |
| Effects on Endogenous Outcomes        |                 |          |          |           |               |
| Own-innovation rate (I)               | 4.1%            | -1.2%    | -1.1%    | 1.7%      | 0.305         |
| Creative destruction by expansion (x) | 0.0%            | 5.0%     | -4.8%    | 0.0%      | 0.188         |
| Creative destruction by entry (z)     | 6.2%            | -19.7%   | 37.4%    | 22.6%     | 0.031         |
| Total creative destruction ( $\tau$ ) | 0.9%            | 1.5%     | 1.2%     | 3.2%      | 0.219         |
| Effects on Equilibrium Moments        |                 |          |          |           |               |
| Life-cycle of markups                 | 3.9%            | -3.2%    | 0.3%     | 5.6%      | 0.1209        |
| Life-cycle of employment              | -1.8%           | 7.7%     | -8.5%    | -4.2%     | 0.4187        |
| Entry rate                            | 2.7%            | -6.2%    | 12.9%    | 9.6%      | 0.096         |
| Growth rate                           | 2.8%            | -0.04%   | -0.1%    | 7.2%      | 0.05          |

Sensitivity matrix for the sample with the all firms. The table summarizes the impact of a %5 change in the parameter values on the endogenous outcomes and equilibrium moments.

To understand the model's sensitivity to changes in parameter values, we undertake an exercise by analyzing the effect of a 5% change in parameter values on endogenous outcomes and equilibrium moments. I will do this exercise only for the sample with all the firms. This exercise aims to understand the intuitive relation between the parameters and their effect on calibrated outcomes. Firstly, a 5% increase in the own-innovation efficiency ( $\varphi_I$ ) causes a 4% increase in the own-innovation rate as expected. On the other hand, it does not impact the creative destruction by expansion since the expansion incentive of firms does not depend on innovation efficiency but rather expansion and entry efficiency. Moreover, we see a significant increase in the creative destruction by entry after the innovation efficiency increases, which acts similar to an invitation since if a firm can enter a market, it can increase its market power at a relatively faster pace so that it can increase the markups that it will gain from that product. However, total creative destruction increases relatively less since it is a combination of both expansion and entry.

Regarding the changes in markups, innovation efficiency corresponds to an increase in the life-cycle of markups as expected, and the increase is close to 4%. On the other hand, the cost of this efficiency can be seen with the decrease in the life-cycle of employment. Now, firms would be less willing to hire workers, and the labor share will decrease too. On the other hand, this innovative efficiency boosts both entry and growth rates. The entry rates will increase since more firms are willing to enter this competition, as mentioned above. Furthermore, we know that the growth rate increases proportionally to total creative destruction and own-innovation rates. Since both of them exhibit positive changes, the growth rate will also increase.

Since we analyzed the effect of innovation efficiency in detail, for the rest of the parameters, I will highlight the more remarkable results. Firstly, an increase in the expansion efficiency of incumbents would slightly decrease the own-innovation rate. In contrast, it significantly decreases the creative destruction by the entry, which is around a decrease of 20%. Such a huge impact is related to the fact that as the expansion of incumbents becomes relatively easier, it makes it less profitable for new firms to enter markets since an expansion of an incumbent can quickly drop them out. On the other hand, since higher expansion efficiency would increase the creative destruction by expansion, the overall creative destruction in the economy will increase too. Regarding the changes in the equilibrium moments, we see that the life-cycle of employment will almost increase 8% as a response to the more efficient expansion. This result is relatively straightforward since expansion directly increases employment. Even though entry reduces, with less own-innovation, the life-cycle of employment will increase. Simultaneously, the life-cycle of markups will also decrease as a response to a lower own-innovation rate.

Secondly, an increase in the entry efficiency will have a similar impact on the own-innovation rate and total creative destruction. However, this time creative destruction by entry will be boosted significantly, whereas creative destruction by the expansion will decrease. Now, incumbent firms feel the danger of creative destruction by entrants more, so they will reduce the expansion rate as a response. Interestingly,

we observe a slight increase in markups in response to higher entry efficiency. This is related to the fact that the decrease in the creative destruction by expansion makes markups increase on average for incumbent firms. On the other hand, the life-cycle of employment is negatively affected by the higher entry efficiency since firms' employment growth is strongly tied up with expansion. The decrease in incumbent expansion would also reduce the life-cycle of employment. On the other hand, the entry rate increases, so there would be more firms smaller in size.

Note that respective increases in the efficiency of both creative destruction channels resulted in a decrease in growth rate. We already know that the model implied growth rate is proportionally increasing with own-innovation and creative destruction. However, even though innovation efficiency also increases total creative destruction, it is not the case with the efficiency of creative destruction channels. That is, own-innovation rate decreases with the higher entry and expansion efficiency. Moreover, creative destruction channels also affect each other negatively. Hence, individual increases in creative destruction parameters would affect growth negatively.

Lastly, an increase in the step size has much more straightforward results on the model dynamics. It increases all outcomes except for the incumbent creative destruction rate, which is related to the fact that step size is not a factor that changes incumbents' expansion behavior. On the other hand, step size increases both markup growth and aggregate growth rate proportionally. This can be seen from the increases in both moments. Furthermore, there would be around a %10 increase in entry rates. However, since the own-innovation rate increased and the expansion rate did not change, the life-cycle of employment would decrease.

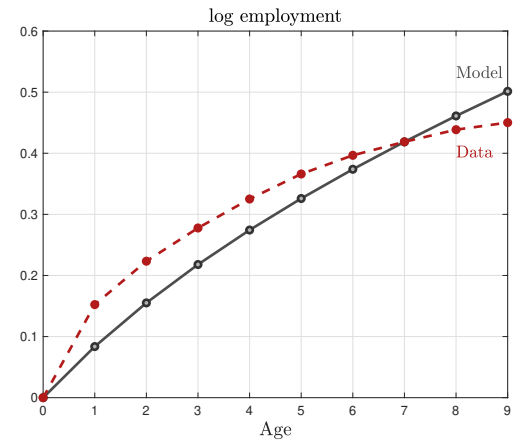
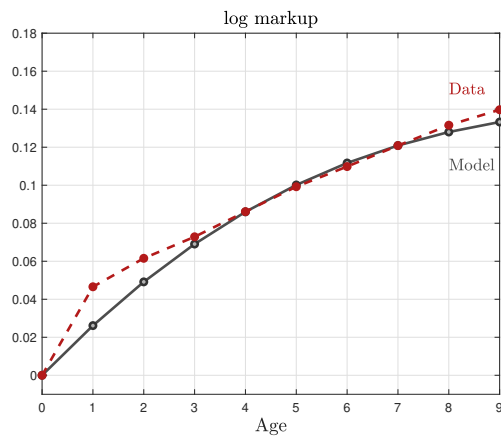


Figure 4. Model vs. data (all firms)

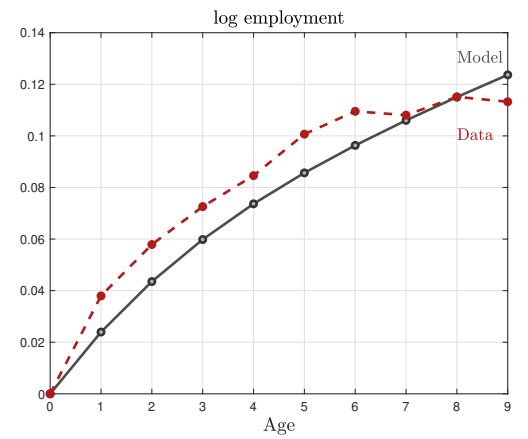
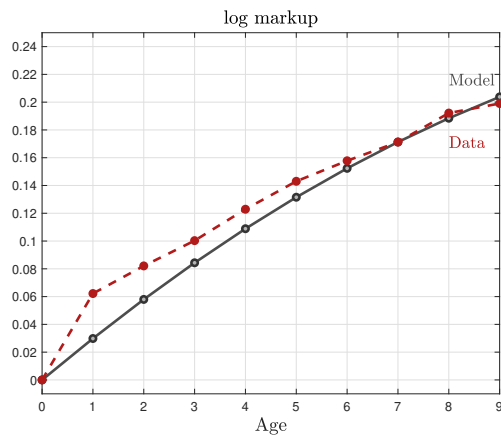


Figure 5. Model vs. data (50+ firms)

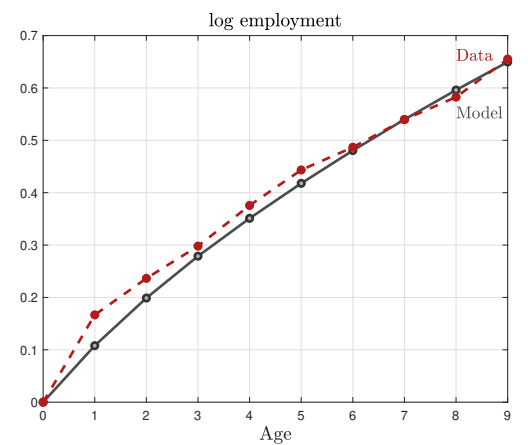
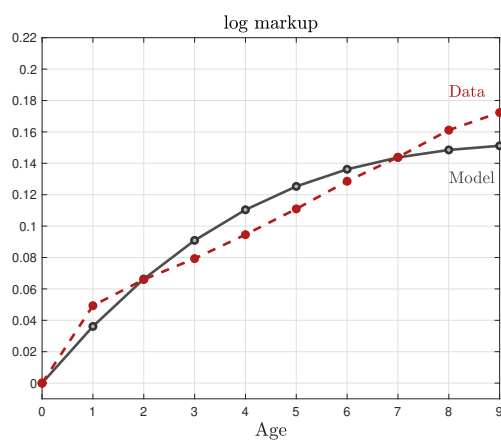


Figure 6. Model vs. data (high tech firms)

#### 4.4 Model versus data

The figures on the previous page show a comparison of the calibrated model and the observed data. Moreover, since we used the cohort age of 7 as a calibration moment, the ages 8 and 9 can be considered non-targeted moments. Hence, the model's fit can be evaluated from that perspective too. Mostly, we see that the model fits with the data. However, sometimes, the increasing pattern does not fit perfectly. For instance, log markup is predicted by the model quite solid for all the firms. However, the data seem to exhibit a concave form for log employment, whereas the model predicts a relatively linear increase in log employment. Similarly, the model implied log employment seems to fit well with the data for the firms with relatively higher technology.

Nevertheless, this time the model implies a concave log markup pattern that the increase of log markup sharply slows down after age 6, and it almost stops after age 8. Actually, when we consider the dynamism of the sample with high technology firms, it is expected that the model implies such a pattern since the creative destruction would limit the markup growth after some age. We already know that a product can survive for a period of  $1/\tau$  in the limit since the destruction occurs at a rate of  $\tau$ . If we also consider the markup increasing own-innovation together with this bounding destruction rate, then we can find the average markup for an old enough firm in the economy; that is, the model gives the average markup by the  $\ln \lambda(1 + I/\tau)$  if a firm lives long enough since this value is exactly the model implied limiting value for the markups. Hence, this limit would get lower as the creative destruction increases relative to the own-innovation (or churning becomes more intense).

In the following sections, firstly, I will share the results for the whole sample to observe the economy-wide dynamics. Then, I will share the individual results for firms with 50+ workers and firms with relatively higher technology. The reason to make this comparison is to gain insights regarding the market power and innovative efficiency relation.

#### 4.5 Markups and misallocation in Turkey

Now, we can focus on the model's implication regarding misallocation. Remember that we have found a unique stationary equilibrium for the given dynamic firm problem, and we have already defined the model's behavior under the static allocation. In this section, we will assume that we reached the model's equilibrium to analyze the welfare implications and how markup behavior affects the TFP and labor share. As a reminder, both misallocation channels can be explained by the shape parameter of the stationary Pareto markup distribution. We derived that the shape parameter is endogenously determined by an endogenous statistic called churning intensity.

Since TFP is not an observable factor, the literature primarily focuses on the TFPR to measure productivity differences, given that prices vary across producers. Now, we will exploit the model's implications over TFPR; that is, the model can explain all the variation in TFPR by the dispersion in markups which can be seen by the below equation

$$\text{TFPR}_{it} \equiv \frac{p_{it}y_{it}}{w_t l_{it}} = \frac{p_{it}q_{it}}{w_t} = \mu_{it}.$$

To support the model implied TFP losses, we can also use the fact that in aggregate, the approximate TFP change would be linked to the TFPR change by the equation  $d \ln \text{TFP} = -\frac{\sigma}{2} d \text{var}(\ln \text{TFPR})$  where  $\sigma$  is the substitution elasticity between different products. Due to our model starting with the assumption of unitary demand elasticity, we take  $\sigma = 1$ . For instance, for the first example, which is on the markups and misallocation relation for the all sample, the  $d \text{var}(\ln \text{TFPR}) = 0.177^2$  and given that  $\sigma = 1$ , we can find the TFP loss of %1.6 which is precisely what the model implies in Table 9.

Next, we analyze through the equilibrium values of own-innovation and creative destruction, which govern the churning intensity (and determine the shape parameter), how the misallocation is formed and how much its' cost to the economy.

Table 9. Markups and Misallocation in Turkey (All)

| Markups and Misallocation |             |                      |       |           |
|---------------------------|-------------|----------------------|-------|-----------|
| $\vartheta$               | E [ $\mu$ ] | $\sigma$ (ln $\mu$ ) | M     | $\Lambda$ |
| 5.66                      | 21.4%       | 0.177                | 0.986 | 0.850     |

The sample for the above analysis includes all of the firms. The table gives the values of the shape parameter of the Pareto distribution of markups,  $\vartheta$ , first and second moments for markups, and the values for the aggregate misallocation measures, namely, aggregate TFP loss, M and labor wedge,  $\Lambda$ . All results emerge given the existence of static equilibrium.

Let us follow the usual order of samples. If we analyze the results for the all sample, the average markup for the economy is founded as 21.4%. On the other hand, Peters (2020) has found the corresponding value as 12% for the Indonesian economy. Nonetheless, the sample that Peters (2020) analyzed was capturing the period of 1990-1998. Moreover, recent studies show an increasing trend in markups over time. For instance, De Loecker et al. (2020) show that their estimation of average markups change significantly between 1980 and 2012 when they analyze the US firms that are open to public trade. The former period indicates a value of 20% for the average markups, whereas when they focus on 2012, they found that average markups increased up to 60%. Another study by De Loecker and Warzynski (2012) implied that markups on the average change between %10 and %28. Considering the markup estimations in the literature, the average value of 21.4% might not be surprising at all. Similarly, the volatility of markups seems to be different from Peters (2020). Our sample has a standard deviation of about 0.18, whereas Peters (2020) found a value around 0.1.

Thereupon, we can concentrate on the main issue, that is, the model implied cost of markups on the TFP and labor share. At first glance, we can observe that the cost is appeared to be quite larger for the labor share. Actually, this result is in line with Peters (2020). The market power manifests itself in labor share much more prominent because the model attributes only a small portion of TFPR variation to the

markups. Remember that the aggregate misallocation on TFP,  $M$ , by definition is shaped by the variation in markups, but the labor share is directly affected by the level of markups. Hence, an increase in the absolute value of markups empowers firms with a relatively higher power to dictate the labor share. We can clearly see these results in the aggregate welfare losses. The TFP loss due to misallocation from markups only reduces the aggregate TFP by around 1.4%. In contrast, the loss in labor share is higher than %15.

Table 10. Markups and Misallocation in Turkey (High Tech)

| Markups and Misallocation |          |                  |       |           |
|---------------------------|----------|------------------|-------|-----------|
| $\vartheta$               | $E[\mu]$ | $\sigma(\ln\mu)$ | $M$   | $\Lambda$ |
| 5.98                      | 20.1%    | 0.167            | 0.987 | 0.857     |

The sample for the above analysis includes firms with relatively high technology. The table gives the values of the shape parameter of the Pareto distribution of markups,  $\vartheta$ , first and second moments for markups, and the values for the aggregate misallocation measures, namely, aggregate TFP loss,  $M$  and labor wedge,  $\Lambda$ . All results emerge given the existence of static equilibrium.

When we focus on the sample with technologically advanced firms, we see similar results to what we observe in the sample with all firms. This time average markups decrease to around 20% with a dispersion of 0.167, and the tail parameter of the Pareto distribution gets slightly higher, which is a result of higher churning intensity. Furthermore, the aggregate TFP loss changes slightly compared to the sample with all firms, and it is decreased by 1%. The main reason for such a slight TFP loss in this specification is mostly related to the highest creative destruction rate that we observe in this sample. Hence, a significant extent of the dispersion is captured due to the high creative destruction rates. Moreover, less market power in this specification also reflects itself in a relatively less aggregate labor share loss, with a value closer to 14%. Still, the impact of market power on the labor share is relatively high compared to aggregate TFP loss.

Table 11. Markups and Misallocation in Turkey (50+)

| Markups and Misallocation |             |                      |       |           |
|---------------------------|-------------|----------------------|-------|-----------|
| $\vartheta$               | E [ $\mu$ ] | $\sigma$ (ln $\mu$ ) | M     | $\Lambda$ |
| 3.70                      | 37.3%       | 0.272                | 0.969 | 0.786     |

The sample for the above analysis includes firms 50+ workers. The table gives the values of the shape parameter of the Pareto distribution of markups,  $\vartheta$ , first and second moments for markups, and the values for the aggregate misallocation measures, namely, aggregate TFP loss, M and labor wedge,  $\Lambda$ . All results emerge given the existence of static equilibrium.

Lastly, we have the most extreme case in our analysis which is coming from the sample of firms with 50+ firms. In this case, the average economy-wide markups go up to %37.3, which is still in the range of De Loecker et al. (2020), but it is pretty higher when compared to the other two specifications. Moreover, the variation in markups also becomes as high as around 0.27. Besides, the aggregate losses due to the market power are more striking. The misallocation in terms of TFP loss becomes around 3%, whereas the loss in the aggregate labor share climbs up to more than %21.

Regarding the significant decline in the labor share, Barkai (2020), and Autor et al. (2017) point out the emergence of superstar firms as a potential linkage to this phenomenon; that is, due to the winner-take-all dynamics of some markets, there might exist some excessively powerful firms. Put differently, in the sample of 50+ firms; we might be observing the results of having relatively higher market power which is a consequence of the winner-take-all type of market structure.

#### 4.6 Counterfactual analysis over entry and expansion costs

In this section, we will compare Turkey with a counterfactual Turkey, which carries all the characteristics except for the entry rate and employment-life cycle dynamics. These two moments will be taken from the U.S. economy, and as a consequence, we will denote this simulated economy as the U.S. With the changes in those two moments, the model will be recalibrated for the entry and expansion efficiency, so the rest of the parameters will stay unchanged. The motivation of this exercise is to observe the importance of the market environment, namely, market barriers that determine the entry and expansion rates. Hence, the model calibration would result in the parameter values for these barriers given the U.S. entry rates and life-cycle of employment. Choosing entry rate and life-cycle employment has an intuitive explanation since they are the most relevant and natural moments to be mapped into by the entry and expansion efficiency. Thus, we try to find the new calibrated efficiency parameters that would give the targeted moments (outcomes) that are implied by the data that we modified in entry rate and employment growth.

What would happen if the Turkish economy had the same entry and employment characteristics as the U.S. economy, given that its characteristic over the innovation characteristic (given the unchanged parameters of  $\tau_I$  and  $\delta$ ) did not change? Hence, we expect to observe the effect of market barriers on the overall economy since the U.S. economy is expected to have a more dynamic and competitive market. Hence, after calibrating the model and finding the market barrier related parameters for the U.S. economy, we will see how these new parameters will change equilibrium outcomes and misallocation. The below table gives detailed information on the model implied changes.

Table 12. Counterfactual Analysis: Turkey vs. U.S.

| Firm Size, Markups, Misallocation, and Growth | Heterogeneous Markups |       |        |
|-----------------------------------------------|-----------------------|-------|--------|
|                                               | Turkey                | U.S.  | Change |
| The Distribution of Firm Size                 |                       |       |        |
| Number of firms (F)                           | 0.322                 | 0.117 | -63.6% |
| Output share of small firms ( $\Omega_1$ )    | 0.141                 | 0.033 | -76.6% |
| Markups, Misallocation and Growth             |                       |       |        |
| Life-cycle of markups                         | 12.1%                 | 7.8%  | -35.5% |
| Average markup                                | 21.4%                 | 14.3% | -33.2% |
| Markup dispersion (products)                  | 17.6%                 | 12.5% | -29%   |
| Aggregate misallocation (M)                   | 0.986                 | 0.993 | 0.7%   |
| Labor wedge ( $\Lambda$ )                     | 0.850                 | 0.889 | 4.6%   |
| Growth rate (g)                               | 5%                    | 5.05% | 0.0005 |

The counterfactual analysis above is done for the sample with all firms. Two moments that naturally indicate the strength of market barriers (entry and expansion efficiency) are recalibrated using the the employment growth and entry rate of the U.S. economy. Rest of the parameters are stayed unchanged. First panel gives the results for the firm size distribution related characteristics and the second panel is related with the markups, misallocation and growth.

Firstly, the results that we found in this counterfactual exercise are quite similar to what Peters (2020) found in his counterfactual exercise between the Indonesian and U.S. economies. Nevertheless, similar to the previous results, the observed impact after recalibrating the model is higher in magnitude. Regarding the firm size, there is a striking decrease in the distribution through a decrease in the firm number of around 63%. This is mainly related to a more efficient market environment. Given that employment growth increases significantly, firms expand more which will cause an equilibrium result of fewer firms that are bigger in size. Also, the entry rate is lower than the value for Turkey since, in the equilibrium, the number of exiting firms is equal to the entering ones. This restriction also lowers the existing firms' exit probability and supports the argument of bigger firms. Peters

(2020) found the corresponding decrease in the number of firms as 60.1% for the Indonesian economy, which is quite close to what we observe in our case. Similar results were also observed in the output share of small firms. It is decreased by more than 75% which indicates that a significant part of the inefficiency is coming from the expansion problems of incumbent problems, that is, with the weaker market barriers, most of the small firms find the opportunity to expand to new product lines, and only a small portion of the firms produce a single product in the U.S. economy.

Moreover, in the U.S. economy, we also see the impact of weaker market barriers as both markups growth and average markups decrease significantly. Both values decreased by more than 30% when compared with the Turkish economy. Remember that as the employment growth increases, we have to have more expanding firms. Given that firms are expanding at a much faster pace, their average markup will decrease significantly too. Hence, given that firms are bigger in size by expanding more and living longer, it is no surprise to observe a decrease in markups related dynamics. Note that markup dispersion also decreases significantly with a more stacked market structure.

Before interpreting the results further, remember that the cost function inherits a term  $\lambda^{-\Delta_i}$  which makes the labor less costly in the own-innovation process for the incumbent firms since the productivity advantage gives them an advantage for further innovations due to accumulated knowledge. Therefore, if a firm follows own-innovation channel dominantly, then the need for labor would decrease so does the employment growth. On the other hand, the theory suggests that firms should be limited in the market power they can accumulate in a competitive environment. Due to the creative destruction, firms would expand to new product lines even though it is more costly in terms of labor cost since it eliminates a bigger problem for firms (exiting the market). Hence, in order to survive in a competitive setting, firms need to expand more eagerly. The effects of the weaker market barriers on the economy are strongly tied with the above arguments.

Next, we can concentrate on the misallocation indicators for the U.S. economy. This new economy has a more dynamic and efficient structure, but it also causes a firm to have less market power. There is a debate in the literature over market concentration and market power relations.<sup>3</sup> Importantly, market concentration does not necessarily imply more market power (Syverson (2004a), Syverson (2004b), and Syverson (2019)). In our example, we see that the market concentration increases as the number of firms decreases and the number of workers in those active firms increases. However, our model does not reflect this result as a consequence of market power, but it is tied up with the efficiency of the economy.

We can support the above arguments through the misallocation channels too. Clearly, both aggregate misallocation in TFP and labor wedge increase in value, and our model implies that under perfect competition, both of the misallocation indicators are equal to 1; that is, the misallocation increases as the misallocation indicators get lower values. In the U.S. economy, aggregate misallocation on TFP reduces by 0.7%. However, since the model implied TFP misallocation was already low due to model structure, this small change actually makes the overall TFP very close to 1. Moreover, the misallocation in the labor share, labor wedge, in the economy decreases by 4.6%. Since firms hire more labor and reduce their markup share, the share of the labor from the aggregate output increases, which is also the result of a more competitive and efficient market structure that the U.S. economy has.

Lastly, we do not see a significant change in the growth rate, which was also the case for Peters (2020), that he found a slight reduction in the growth rate. In our case, there is a 0.1% increase in the growth rate. Considering that higher creative destruction disincentivizes firms' own-innovation investments, the model implies that the effect of creative destruction is strong enough to get the edge and result in a vaguely higher growth rate.

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<sup>3</sup>For instance, Aghion et al. (2022) used a different extension of Klette and Kortum (2004) and showed that the firms' ability to expand into multiple markets is the source of the market power and also caused the market concentration, but note that in their study firms' have heterogeneous permanent process productivity levels that they can carry over in each product line that they extend. Nevertheless, in Peters (2020), an incumbent's expansion to a new product line always results in a one-step improvement of the previous productivity level of that product line.

Table 13. Counterfactual Analysis: Turkey (50+) vs. U.S.

| Firm Size, Markups, Misallocation, and Growth | Heterogeneous Markups |       |        |
|-----------------------------------------------|-----------------------|-------|--------|
|                                               | Turkey                | U.S.  | Change |
| The Distribution of Firm Size                 |                       |       |        |
| Number of firms (F)                           | 0.609                 | 0.122 | -80%   |
| Output share of small firms ( $\Omega_1$ )    | 0.397                 | 0.035 | -91.2% |
| Markups, Misallocation and Growth             |                       |       |        |
| Life-cycle of markups                         | 17.1%                 | 6.3%  | -63.2% |
| Average markup                                | 37.3%                 | 13.6% | -63.5% |
| Markup dispersion (products)                  | 27.1%                 | 12%   | -55.7% |
| Aggregate misallocation (M)                   | 0.969                 | 0.993 | 2.5%   |
| Labor wedge ( $\Lambda$ )                     | 0.786                 | 0.893 | 13.6%  |
| Growth rate (g)                               | 5%                    | 5.39% | 0.0039 |

The counterfactual analysis above is done for the sample of firms with 50+ workers. Two moments that naturally indicate the strength of market barriers (entry and expansion efficiency) are recalibrated using the the employment growth and entry rate of the U.S. economy. Rest of the parameters are stayed unchanged. First panel gives the results for the firm size distribution related characteristics and the second panel is related with the markups, misallocation and growth.

The above table shows the results of the same counterfactual analysis that is done previously but this time for the firms with 50+ workers. We already witnessed that sample with larger firms gave less efficient outcomes, both in terms of markup and employment growth. Hence, it is no surprise that transforming this inefficient structure into a more competitive counterpart will have observable positive outcomes. Hence, in this exercise, we have more extreme results than the all sample case. Through a quick glance, we can see that the number of firms decreased 80%, with the output share of small firms decreasing more than 90%. These outcomes point out the severe misallocation in the firm size distribution.

Nevertheless, as a reminder, weaker market barriers did not cause these outcomes directly by themselves. As a result of these weaker market barriers, all the

market power accumulation dynamics of the model changed. In this significantly more competitive environment of the U.S., there is no room to accumulate market power as much as in the Turkey case. Hence, the optimal strategy for firms to expand and increase the probability of survival in this highly dynamic business environment. Moreover, since the markups distribution is the equilibrium outcome of the model given the market power characteristics, markups related outcomes decreased by around 60%. Market power related measures indicate a significantly less misallocation than the initial case with a significant boost to growth rate compared to all sample case. All these results might show the inefficiency of the upper echelon firms in Turkey since one expects firms with 50+ workers are actually the sample with the highest market power. Clearly, putting this inefficient sample in a more competitive setting results in remarkable changes. Hence, the worries regarding the market barriers which extend the power of inefficient firms even further might be a valid point that we should consider to understand competition dynamics in Turkey.

## CHAPTER 5

### CONCLUSION

The effect of misallocation on various economic outcomes are analyzed as the misallocation is regarded as exogenous. In the model of Peters (2020), market power is determined endogenously within the model, and the markup behavior of the firms results in an equilibrium outcome. The most crucial statistic in this setting is the churning intensity or the rate at which own-innovation occurs relative to creative destruction. From the point of view of recent literature on business dynamism (Autor et al. (2017), Akcigit and Ates (2019), De Ridder (2021), Aghion et al. (2022), Olmstead-Rumsey (2022)), a weaker churning intensity would correspond to a slowdown in business dynamism and an environment that offers higher market power for incumbent firms which in turn will enable those firms to increase their monopolistic rents in terms of the markups. However, in a more competitive setting, the Pareto distribution of markups would have a thinner tail, and misallocation would be less than in the previous case.

When we implement the model in Turkey with different specifications, especially, the sample with firms with 50+ workers indicates the existence of an enormous monopolistic power with very high markup growth and slight growth in employment. This result reflects itself in the misallocation dynamics, mainly with the significant decrease in the labor share, which corresponds to a labor wedge of around 21%. Nevertheless, when we analyze all the firms in Turkey, we again see a markup growth with a relatively high slope, but employment growth also has a higher slope relative to the case with larger firms. Still, the labor wedge for all firms sample is 15%. Regarding the losses in aggregate TFP, we observe relatively smaller values due to the model's implication on the TFPR and TFP linkage. Given that markups are the only cause of the misallocation in the economy, aggregate TFP reduces by around 3% for the larger firms sample and around 1.4% for the all sample. Edmond et al. (2022) found a misallocation on TFP due to markups as around 2% and 6% for the U.S.

In the last exercise, the Turkish economy is compared with a simulated U.S. economy which essentially inherits the entry and expansion dynamics of the U.S. economy. The results pointed out that the market barriers act as a mechanism that gives extra strength to the incumbent firms as the theory predicted. When the market barriers become weaker, the number of firms decreases significantly. However, most firms that are quitting the market are arguably inefficient ones that only operate in a single product market. The model implies that in a competitive economy firms need to expand due to high level of dynamism, so many firms producing a single product can be viewed as a less competitive market where firms invest into accumulate more market power. The results indicate that for the all firms sample, the number of firms decreased by around 64%, and the output share of firms that produces only a single product also decreased by more than 75%. As a side note, the results that we found for the all sample case in the counterfactual analysis strongly resemble the results that Peters (2020) found in his experiment with the Indonesian economy. As expected from the previous results, the effect of weaker market barriers had a larger impact on the sample with 50+ firms. Moreover, even though this counterfactual economy caused higher market concentration, it does not correspond to higher market power which can be seen by the decrease in the level of aggregate misallocation in the economy. This argument was also supported by Syverson (2004a), Syverson (2004b), and Syverson (2019). The U.S. economy also had higher growth rates which also underpins the more efficient and competitive market environment argument.

Lastly, Turkish economy seems to suffer from a decline in the labor share, but the underlying reasons might be different than the labor share decline for the U.S. economy (Autor et al. (2017) and Autor et al. (2020))

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