Essays on Human Capital Accumulation and Development

By

Hyunseok Kim

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The dissertation is approved by the following members of the Final Oral Committee:

Ian Coxhead, Emeritus Professor, Agricultural and Applied Economics

Laura Schechter, Professor, Agricultural and Applied Economics

Paul Dower, Associate Professor, Agricultural and Applied Economics

Thomas Rutherford, Professor, Agricultural and Applied Economics

Menzie Chinn, Professor, Robert M. La Follette School of Public Affairs

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Introduction

In this dissertation, I explore human capital accumulation and its implication for economic development. Chapter 1 and 2 focused on the mechanism behind the sustained economic growth of South Korea, which was a war-devastated, aid-recipient country two generations ago but now sells semiconductors and automobiles to the world. I ask how the country shifted its technology to capital-intensive production technique. These chapters consider educational policy change that led to an increase in college graduate. Chapter 3 studies the mechanism behind the divergence in employment between temporary and permanent workers in South Korea. The chapter considers the labor policy change that protects temporary employment. For each chapter, I construct a plant-level panel dataset from a series of censuses and connect it with an industry-level input-output table to consider a spillover effect.

Chapter 1 studies how an increase in college graduates has affected the technology shift in South Korea. The analysis is based on the concept of complementarity in technology adoption – i.e., the idea that more adopters increase a marginal adopter's gain. I consider skilled labor as an adoption good needed for technology adoption. If complementarity exists in technology adoption, there could be multiple equilibria, possibly leading to undesirable results from coordination failure. I develop a theoretical framework which predicts that an increase in the adoption good of skilled labor could overcome coordination failure and promote a technology shift. Based on plant-level panel data from 1982-1996, I find that accumulation of more outside human capital, or more adopters, (i) benefits marginal adopting firm's profit and investment, and (ii) promotes the firm's technology shift by increasing the productivity of capital while decreasing that of unskilled workers. This paper contributes to the literature on aggregate growth theory by verifying that outside human capital accumulation and its spillover effect contribute to economic growth.

Chapter 2 builds on Chapter 1, where human capital is considered an adoption good, by studying the specific role of human capital. Specifically, I explore whether research and development (R&D) is the channel through which human capital accumulation leads to a technology shift. The analysis is based on previous literature indicating that R&D generates new knowledge and the absorption of outside knowledge. The latter role of R&D, absorptive capacity, matches the concept of complementarity in chapter 1. Based on plant-level panel data, I find that (i) human capital accumulation due to the educational policy change promotes R&D in the manufacturing industries; (ii) the effect of R&D spillovers is increasing in a firm's own R&D, a finding which validates the concepts of absorptive capacity and complementarity; and (iii) more outside R&D promotes a firm's technology shift toward capital-intensity. This paper contributes to the literature on endogenous growth, which so far has focused on R&D spillover's effects on total factor productivity rather than on technology shift, by connecting absorptive capacity with complementarity in technology adoption.

Chapter 3 investigates another dimension of human capital: permanent and temporary workers. The labor market in South Korea has witnessed a divergence in employment between permanent and temporary workers. The proportion of permanent workers, which had been stable between 50 and 60 percent for two decades in the 1990s and 2000s, has increased recently to above 70 percent. I point out that legislation requiring firms that hire a worker on a temporary basis for more than two years to offer them permanent status serves as a trigger for the divergence. This legislation limits the advantages (to firms) of flexibility in hiring and capacity for screening new workers. Hence, in a competitive labor market firms expect that other firms are more likely to hire permanent rather than temporary workers. If complementarity exists in permanent employment, the legislation serves as a Big Push to make the divergence happen. Based on plant-level panel data covering 2011-2019, I find that (i) flexibility and screening effect of temporary workers are overwhelmed by human capital effect, and (ii) complementarity in permanent employment holds after the temporary employment protection legislation. This paper deepens the understanding of the recent labor market phenomena in South Korea by adopting the concept of complementarity and a Big Push.

Chapter 1

Human Capital, Technology and Sustained Growth in South Korea

1.1 Introduction

In this paper, I verify a determinant of sustained economic growth in South Korea. Within two generations, South Korea went from a war-devastated, aid-recipient country to one of the wealthiest countries in the world, producing automobiles, semiconductors, and container ships. How did this change happen? According to traditional growth theory, such as the Solow model (1956), factor accumulation causes economic growth of a country, but diminishing returns make it difficult for the country to maintain growth. On the other hand, Ventura (1997) argued that countries open to the world market can overcome diminishing returns through structural change toward capital-intensive industries or techniques. South Korea's success has been a process similar to that proposed by Ventura. However, I argue, more specifically, that increased human capital accumulation outside a firm helps overcome coordination failure and facilitates the firm's technology shift toward capital-intensity.

Human capital (or skilled workers) is needed for firms to adopt capital-intensive technology. In developing countries, manufacturing technology is traditionally intensive in the use of unskilled workers. Advanced (or modern) technology, however, will convert intermediate inputs into more output with the same number of unskilled workers, so modern technology can be considered as intermediate goods-intensive. Skilled workers are needed to adopt this modern technology. Skilled workers enable the firm to conduct research and development (R&D) and to introduce and operate advanced machinery and equipment. Hence, modern technology is also skilled labor- and capital-intensive.[1]

By acknowledging the role of intermediate goods in the production process, I develop a detailed explanation of inter-industry relationships and *complementarity in technology adoption*:[2] In brief, if upstream industries have more skilled workers or technology adopters, low-price or high-quality intermediate goods are available, and so the marginal adopter who adopts intermediate goods-intensive technology benefits more. If complementarity exists in technology adoption, then more adopters in upstream industries promote an individual firm's technology shift toward modern technology, but if there are not enough adopters outside a firm, the firm will not adopt modern technology. Hence, complementarity in technology adoption could lead to multiple equilibria. If coordination fails, the country could reach an undesirable equilibrium in which all firms are stuck in the traditional technology. How, then, can a country prevent coordination failure and achieve a desirable status?

I argue that two conditions are needed to overcome coordination failure when complementarity in technology adoption is possible. First, domestic industries must be closely connected to each other so an increase in skilled labor in other industries can affect firms buying intermediate inputs from these industries. This condition exists in South Korea because the

[1] See Goldin and Katz (1998) for evidence of technology-skill complementarity and capital-skill complementarity.
[2] The concept of complementarity indicates that more adopters increase a marginal adopter's gain.

government enacted *legislation*[3] in 1975 to set up a structure of specialization[4] and to promote long-term cooperation between *chaebol*[5] and small and medium enterprises (SMEs). *Chaebol* were encouraged (or guided) to contract intermediate goods out to SMEs and to build long-term relationships with SMEs. This act helped small Korean suppliers in manufacturing industries to secure a stable demand market and grow (Lee et al., 2017).[6]

Second, there should be a big increase in the number of skilled workers flowing (or hired) into the upstream industries. Traditional unskilled labor-intensive technology in developing countries does not need much skilled labor input, so people demand less tertiary education to become skilled workers. But without domestic human capital accumulation, the country is likely to experience complementarity-induced coordination failure in technology adoption, and is therefore unlikely to shift toward capital-intensive technology. South Korea, however, has had excess demand for tertiary education even at the initial stage of the development process. Moreover, an education policy change in 1981 dramatically increased the number of college graduates. Prior to the policy change, the government established a college enrollment quota which limited the number of places each major in each university could offer each year. The government tended to maintain the quota until the late 1970s and began to favor increasing the quota after that (Kim, 2021). In 1981, the government revised educational policy to expand the college enrollment quota by 30 percent, resulting in a remarkably increased number of college admissions. The relaxation of the college enrollment quota and subsequent surge in the supply of skilled workers starting in the mid-1980s enabled firms in manufacturing industries to hire more

[3] Act on the Promotion of Cooperation between Large Enterprises and Small and Medium Enterprises (1975).
[4] A system in which *chaebol* produce final goods by using intermediate goods produced by domestic SMEs.
[5] Family-controlled big businesses in South Korea, such as Samsung, Hyundai, SK, and LG.
[6] As Krugman and Venables (1995) state, South Korea achieved an agglomeration economy that equipped both upstream and downstream manufacturing industries and transitioned from a peripheral to a core country, i.e., one that exports capital-intensive goods, to the world economy.

skilled workers. In this paper, I treat the relaxation of the college enrollment quota since the early 1980s and the consequent increase in skill ratio in upstream industries as key factors for the improved intermediate inputs and the following technology shift toward capital-intensive technology. This process decreased the price of the downstream exporting firm, enabling price competitiveness in the world market.

This study constructs a theoretical framework of complementarity in technology adoption and also provides empirical evidence to support the model in the paper. I show that more skilled workers (or more adopters) in the upstream industries promote a firm's *technology shift* by increasing the elasticity of value-added with regards to capital and skilled labor while decreasing that with regards to unskilled labor between 1982-1996. As the marginal productivity of capital keeps increasing, and so does the demand for capital due to the outside skills, the country has more chance to delay diminishing returns in the development process and the following accumulation of physical capital. This paper also verifies the *complementarity in technology adoption* itself which is the major momentum with which human capital accumulation in upstream industries facilitates individual firms' technology shift. I show that beyond the certain point of skill ratio in the upstream industries, the effect of a firm's hiring skilled labor on investment and profit turns positive and the effect on price turns negative. The break-even point for each outcome turns out to be stable, or robust, with the additional controls for firm- and industry-level productivity, profitability, and trade in the paper. To sum up, human capital accumulation in the upstream industries leads to a decrease in price of intermediate inputs, and promotes a firm's technology shift toward capital-intensity to maximize the benefit from intermediate inputs.

My approach to verifying complementarity in technology adoption has two benefits: First, it considers the spillover effect of skills in the industries that supply intermediate goods. Second, it will explain how much of an increase in human capital makes a difference in productivity. Without a massive increase in skills, upstream industries will be scarce in skills and their intermediate goods will not become cheaper, so the number of skills in each firm will be less likely to affect modern technology adoption. It is more likely for developing countries to be stuck in the development process due to this concept of complementarity in technology adoption.

My study provides a rich explanation of economic growth in South Korea. First, it shows human capital accumulation has an important role, and especially, spillover effect of human capital accumulation outside a firm matters. The study examines that more outside human capital accumulation increases a firm's benefit to hiring human capital and promotes a firm to adopt capital-intensive technology. This spillover effect of human capital accumulation, itself, tells about the chance of constant or increasing returns (Lucas, 1988; Gemmell, 1998), or at least a momentum to delay diminishing returns. Second, the aforementioned spillover effect is shown to occur through the channel of intermediate goods in the well-connected upstream-downstream structure in South Korea. So far, most studies have found that human capital accumulation has served as a major determinant of economic growth in South Korea (Sengupta and Espana 1994; Lee et al. 1994; Piazolo 1995; Kang 2006; Harvie and Pahlavani 2006; Maksymenko and Rabbani, 2008). These studies, however, do not focus on the channels through which human capital accumulation has an impact on economic growth. Some studies point out that human capital accumulation affects other production inputs like physical capital as well as total factor productivity growth (Benhabib and Spiegel, 1994; Lee, 2007) I pay attention to input-output linkage in manufacturing industries and provide empirical evidence that outside human capital accumulation enhances a firm's technology shift and helps lower the price of its product. Third, my study points out that outside human capital accumulation affects the technology shift toward capital-intensity, not total factor productivity (TFP). The strategy of not focusing on TFP growth is in accordance with other renowned studies showing that a key factor for East Asian Miracle is not TFP growth but factor accumulation (Kim and Lau, 1994; Krugman, 1994; Young, 1995; Collins, Bosworth, and Rodrik, 1996). Indeed, my explanation of economic growth in South Korea can be thought of as a consolidation of two main views in aggregate growth theory. I adopt outside human capital accumulation as a key momentum which is analogous to new growth theory, but I show that outside human capital accumulation leads to a technology shift toward capital-intensive so that it increases the demand for capital and delays diminishing returns that is a key concept in the neoclassical growth theory. Lastly, my study gives an explanation of South Korea's economic growth after the termination of the government-led industrial policy in the late 1970s. Recent studies (Lane, 2021; Kim, Lee, and Shin, 2021) evaluate industrial policy promoting heavy-chemical industries in the 1970s. However, there is no notable study focusing on the momentum of economic growth in the 1980s and 1990s. I build a linkage between education policy and economic performance to explain sustained growth in South Korea.

The paper is organized as follows. Section 1.2 reviews previous literature. Section 1.3 describes the contextual factors of South Korea. Section 1.4 develops a theoretical framework to show how human capital accumulation in upstream industries can affect a specific firm's technology shift toward capital-intensity. Section 1.5 describes the data, Section 1.6 presents the specifications, and Section 1.7 is discussion and conclusion.

1.2 Literature Review

1.2.1 Aggregate growth literature: accumulation versus assimilation

Many studies have tried to shed light on the major determinants of economic growth in East Asian countries, especially South Korea, Singapore, Taiwan, and Hong Kong. These countries, also known as the East Asian Tigers, have shown sustained growth over two generations and have caught up with advanced economies. Many researchers call these countries' sustained growth the "East Asian Miracle". Much of the debate about the key factors in their growth dwells on the views of assimilation and accumulation. The assimilation view says that total factor productivity (TFP) growth leads to sustain economic growth in East Asian countries. One of the assimilation views suggests that learning from imported technology was the key factor for East Asian countries' catch-up (Amsden, 1992). The World Bank's renowned report, "East Asian Miracle", states that human capital and export-oriented growth policy in these countries boosted technological upgrading, and the countries, therefore, achieved rapid productivity growth (Birdsall et al., 1993). The accumulation view, on the other hand, points out that TFP growth in East Asian countries has been moderate, and physical capital accumulation is a key factor in these countries' catch-up (Kim and Lau, 1994; Krugman, 1994; Young, 1995; Collins, Bosworth, and Rodrik, 1996). But this point of view must address how the country has managed diminishing returns on capital in the development process. It is difficult because physical capital becomes more abundant as it is accumulated in the process of economic growth, and the excess supply of physical capital leads to a decrease in the rate of return on capital. Ventura (1997) explains how the East Asian Tigers delayed diminishing returns on capital. These countries changed the structure of production: they absorbed the extra capital by expanding the physical capital-intensive sector and selling physical capital-intensive goods to the world market.

There is, however, no explanation of how to expand the physical capital-intensive sector. Ventura's (1997) model assumes elastic supply of labor, but it does not consider skilled labor (or human capital) separately. If skilled labor and physical capital are complements, and supply of skilled labor is inelastic, it would induce diminishing returns. On the other hand, if a supply of skilled labor promotes a firm's technology shift toward capital-intensity, the country could delay diminishing returns.

1.2.2 Trade and human capital as key factors for South Korea's catch-up

In the above debate dwelling on accumulation versus assimilation, it seems that both trade and human capital played important roles in South Korea's economic growth. The government of South Korea pursued export-led economic growth. Also, modern technology imported from advanced countries promoted economic growth through the learning process. Moreover, human capital accumulation is a critical factor in the process of learning advanced technology as well as adopting advanced equipment.

Conolly and Yi (2015) find that tariff reduction in South Korea and G7 countries influenced South Korea's economic performance through imported investment and vertical specialization by simulating outputs without these two channels and comparing them to actual outputs. Their finding is consistent with Estevadeordal and Taylor (2013), who find imported capital and intermediate inputs are key channels through which trade liberalization affects economic growth. The research states that tariff reductions in both South Korea and G7 countries account for about 17% of South Korea's actual catch-up to G7 countries (Conolly and Yi, 2015). Trade liberalization therefore partially explains South Korea's sustained growth. It is worth, however, asking where the remaining 83% of South Korea's catch-up comes from. Human capital accumulation can be a key source of catch-up, or sustained growth, in South Korea.

Many theoretical studies try to explain the effect of human capital accumulation on endogenous TFP growth, but they are not successful in explaining East Asian countries' catch-up. Human capital is accumulated differently from producing specific goods through learning-by-doing, and it leads to TFP growth (Lucas, 1988). Similarly, human capital devoted more to research in the area with more stock of knowledge leads to more efficiency in producing new knowledge and goods, and this process allows TFP growth (Romer, 1990). These theories expect divergence among countries, i.e. the rich-get-richer and the poor-get-poorer, and thus, they do not support East Asian countries' catch-up with advanced economies. Also, East Asian countries have shown moderate TFP growth in their development process (Kim and Lau, 1994; Krugman, 1994; Young, 1995; Collins, Bosworth, and Rodrik, 1996). Mankiw et al. (1992) include human capital in the Solow Model (1956) and see whether there are nondecreasing returns on total capital, the sum of physical and human capital, but the study fails to reject the hypothesis of decreasing returns.

The empirical literature focusing on South Korea does not fully explain the country's sustained growth nor does it specify the channel through which human capital accumulation affects South Korea's catch-up. Some empirical studies apply time series analysis and find that human capital accumulation has a significant positive effect on South Korea's long-term growth (Harvie and Pahlavani, 2006; Maksymenko and Rabbani, 2008). But these studies do not explain the channel through which human capital accumulation affects sustained growth in South Korea. Kang (2006) adopts the approach of Mankiw et al. (1992) with data from South Korea and also fails to find nondecreasing returns to scale in the total physical and human capital. This indicates that economic growth in South Korea is doomed to converge and the author cannot fully explain the country's sustained growth. According to Lee (2007), however, growth accounting does not consider that human capital stock affects the growth of the other inputs as well as technological progress. Benhabib and Spiegel (1994), using cross-country data, also show that the initial level of human capital stock is positively associated with (i) physical capital accumulation and (ii) total factor productivity growth.

Che and Zhang (2018) examine the effect of the education expansion in China and conclude that human capital accumulation in China has a positive effect on the firm's productivity, but some questions remain unsolved. The authors use the difference-in-difference method and find that there was no significant difference in total factor productivity between skill-intensive (i.e., college graduate-intensive) and non-skill-intensive (i.e., college graduate-less intensive) industries before the expansion of college education in the early 2000s. But after the education expansion, skill-intensive industries show higher productivity than skill-non-intensive industries. One question that emerges is why there is no significant difference with regard to the productivity between skill-intensive and skill-non-intensive industries before the expansion of college education. The authors explain it by assuming that there are threshold amounts of skills needed so that skills can affect productivity, and argue that there were initially not enough amounts of skills (i.e., college graduate workers) in the skill-intensive industries. After the education expansion, the authors argue that skill-intensive industries satisfied the level of skills threshold so that skills can affect productivity in these industries. But the authors do not explain the specific level of the threshold itself. Also, since they do not use an actual ratio of skills in each Chinese industry but rather use the ratio of skills in the United States in 1980 as a benchmark, they do not show how much each skill-intensive industry is able to attain the threshold from education expansion.

In my study, I analyze the effect of the expansion of college education in the early 1980s in South Korea by considering the concept of complementarity in technology adoption. I do not use a threshold of skill ratio in each industry as Che and Zhang (2018) assume. Rather, I verify the overall threshold of skill ratio in the upstream industries to conclude that there is complementarity in technology adoption. The expansion of college education will affect not only the single industry to which a firm belongs but also the industries from which the firm buys its intermediate inputs. By adopting this approach, I can calculate what fraction of skills in the upstream industries are needed for the firm that hires skilled workers to turn positive profits. This approach adopts the concept of complementarity in technology adoption to explain why there is a technology shift after the expansion of college education in South Korea. The simple way of explaining complementarity in technology adoption is that more adopters increase the marginal adopter's gain, and so the marginal adopter will adopt an advanced technology when there are more adopters in the upstream industries. When there is the expansion of college education, more skills flow into industries that supply intermediate goods. Since skilled workers can be thought of as adoption good for productive advanced technology, each firm believes that the price of intermediate inputs will be cheaper when more skilled workers are flowing into upstream industries. So, for the firm, it is more beneficial to adopt modern technology that converts intermediate inputs to more output with the same number of unskilled workers so that the firm can get the best out of the cheaper intermediate goods.

My paper has its roots in three distinguished works of literature: Ventura (1997), Krugman and Venables (1995), and the Big Push theory. My paper connects these pieces of literature cohesively and contributes to explaining South Korea's sustained economic growth by adopting outside human capital accumulation as a key factor.

Ventura (1997) argued that South Korea delayed diminishing return on capital by expanding capital-intensive industries and trading away capital-intensive goods abroad. Verifying the channel through which the country can delay diminishing returns on capital is a prominent area as many developing countries have not been successful in maintaining economic growth. There is no clear explanation in Ventura (1997), however, on how to expand the physical capital-intensive sector and how to maintain price competitiveness to continuously trade away physical capital-intensive goods.

Krugman and Venables (1995) explained how a country can achieve these two by modeling the linkage between upstream and downstream industries. Industrial policy, such as building a shipyard or an auto factory, entices firms in upstream industries since they can sell their products as intermediate goods for the firms in downstream industries (i.e., backward linkages). As upstream firms increase, the downstream firm can save costs by using its bargaining power (i.e., forward linkages). This virtuous cycle makes it possible for the country to enjoy economies of scale, and catch up to the advanced economies. This kind of industrial policy toward expanding the physical capital-intensive sector is widely used in many countries, but only a few countries including South Korea have successfully climbed up the production ladder. To achieve both forward and backward linkage effects, upstream firms that produce intermediate goods need to be productive so that buyer firms would procure intermediate goods from them. However, there is a chance of complementarity in technology adoption: more adopters will increase the gain to a marginal adopter. This can therefore lead to coordination failure, which can explain the reason many developing countries are stuck in traditional less-productive technology.

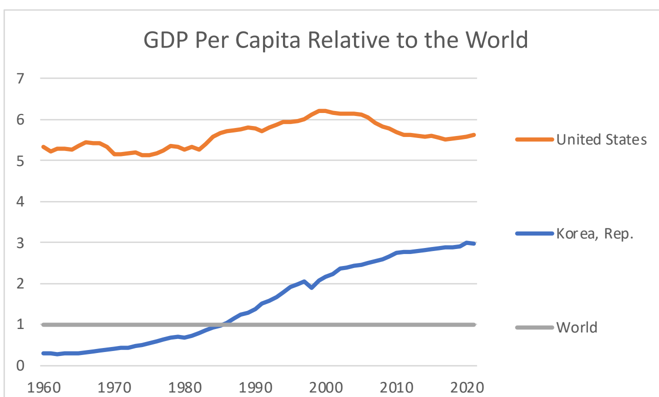
I borrow a Big Push model from Murphy et al. (1989), Sachs and Warner (1999) and Buera et al. (2021), and modify it by applying skilled labor as an adoption good for modern technology to focus on human capital accumulation and overcoming coordination failure. Since the expansion of the college enrollment quota in the early 1980s was huge in scale and industry-wide in range, a decision-making firm's expectation becomes more optimistic as the firm expects more and more upstream firms to adopt modern technology and produce their output cheaper, which is intermediate input for the decision-making firm. It increases the decision-making firm's expected future profits, and the firm that maximizes the present value of future profits, thus, chooses to adopt modern technology which is capital-intensive. Hence, this study examines outside human capital accumulation promotes a firm's technology shift toward capital-intensity so the country can delay diminishing returns and sustain export-led economic growth.

Recent studies shed light on the evaluation of industrial policy promoting heavy-chemical industries in the 1970s in South Korea (Lane, 2021; Kim et al., 2021). My paper focused on the post-industrial policy era of the 1980s and 1990s and provides a rich explanation of sustained growth by highlighting the role of outside human capital accumulation and verifying complementarity in the technology shift toward capital-intensity.

1.3 Context of South Korea

South Korea experienced a dramatic transition from one of the poorest countries to one of the rich countries within two generations. The country was one of the poorest in the world at the end of the Korean War (1950-1953). As a result of this war, about 10% of the population of the Korean peninsula died or was injured, the peninsula was completely devastated, and most of its production facilities were destroyed (Lee, 2007). The country, however, has been successful in economic growth from the war-devastated, aid-recipient status, and the country now gives aid to other countries and sells high-tech products like semiconductors, automobiles, and container ships to the world. The country's Gross Domestic Product (GDP) per capita[7] was about $33,000 in 2021, which is more than a half of the GDP per capita in the United States and three times as much as the global GDP per capita. It is a quite surprising phase of development since South Korea's GDP per capita was about $1,000 in 1960, which was about a twentieth of the GDP per capita in the United States, and a third of the world at the same time, as shown in Figure 1.1.

Figure 1.1: GDP per capita relative to the world for South Korea and the United States



Source: World Bank (2023), constant 2015 US$

[7] GDP per capita (constant 2015 US$) in South Korea: (1960) 1,027 -> (2021) 32,731
In United States: (1960) 19,135 -> (2021) 61,856
In the World: (1960) 3,597-> (2021) 11,011

1.3.1 South Korea's Economic Growth in the 1960s and 1970s

What sustained the continued growth of South Korea's export-led economy? As a small open economy, South Korea achieved rapid growth during the 1960s by exporting manufacturing goods such as textiles, apparel, and footwear (Amsden, 1989). In 1964, the value of the country's exports was $100 million. The country achieved an export of $1 billion in 1970, which means it took only six years to increase tenfold. A country whose chief export of textiles, garments, and footwear is, however, apt to lose its competitiveness by competing against other developing countries with lower wages. (Park et al., 2013).

The Korean government came up with a policy to promote heavy-chemical industries (HCI) in the 1970s. The government aimed at achieving $10 billion in exports and $1,000 in GDP per capita (current US$) in 1981 by boosting HCI, and the country reached the goal successfully.[8] This industrial policy, however, did not survive beyond the 1970s. After the assassination of President Park in 1979, the Korean government focused more on adjusting the excessive investment and resource allocation on HCI conducted in the 1970s by adopting a market-oriented approach (Lane, 2021). Then what were the key factors for the growth in the post-industrial policy era of the 1980s and 1990s?

[8] The Korean government's promotion policy for the six targeted HCI ended in 1979 since the country accomplished its goal of $10 billion export and $1,000 GDP per capita (current US$) in 1977, four years prior to the initial target year of 1981. After 1979, the government adopted a market-based approach since *chaebol* in HCI matured enough to operate on their own, but the government still managed the banking system to control *chaebol*. This trend continued until the Asian Financial Crisis in 1997 (Park et al., 2013).

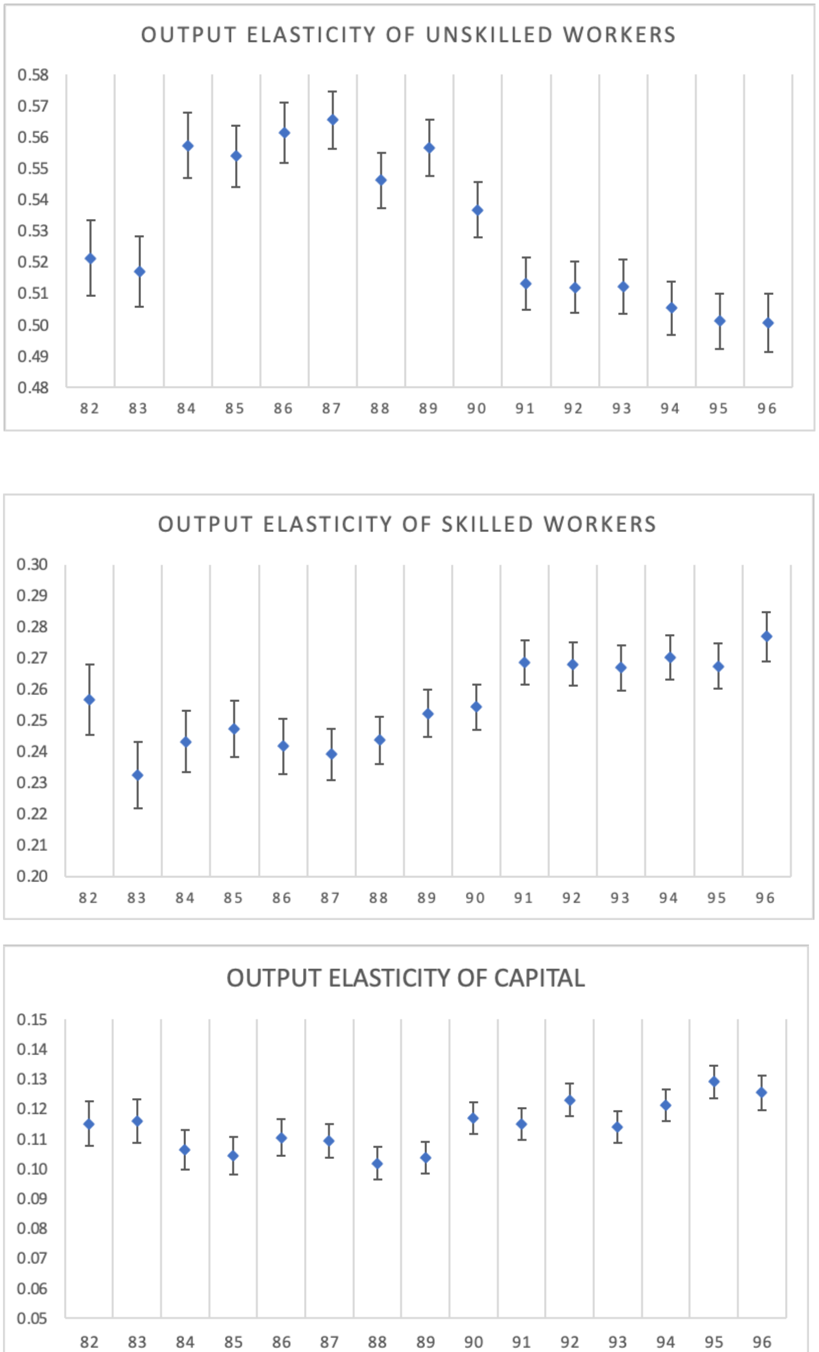
1.3.2 Economic Growth in the Post-Industrial Policy era of the 1980s and 1990s

Since the mid-1980s, there has been an increase in the contribution of capital and skilled workers to total manufacturing output, and a corresponding decrease in that of unskilled workers as shown in Figure 1.2. The country has indeed, achieved a shift from traditional unskilled-labor intensive toward capital-intensive technology. Most developing countries aspire to make such a shift but relatively few have succeeded, especially in such a dramatic way. As the literature explains there is complementarity in technology adoption, and so there is a chance of coordination failure (Rosenstein-Rodan, 1943; Murphy et al., 1989; Buera et al., 2021).[9]

My argument is that under the closely connected manufacturing industries, the expansion of the college enrollment quota and the resultant huge and wide increase of human capital accumulation in the upstream industries is a policy shift with effects equivalent to those of a ‘big push’. The expectation of an increase in the supply of skills gives an optimistic expectation to a firm that other firms in upstream industries will adopt modern technology and improve their output. It is more beneficial for the firm to adopt modern technology since modern technology maximizes the benefit of improved intermediate inputs. The firm, hence, chooses to adopt modern technology, and the country can overcome coordination failure. It is worth reviewing the country’s two special conditions at that time for overcoming the coordination failure in technology adoption: a closely interconnected industrial ecosystem, and the expansion of the college enrollment quota.

[9] Agents are to be stuck in the undesirable equilibrium.

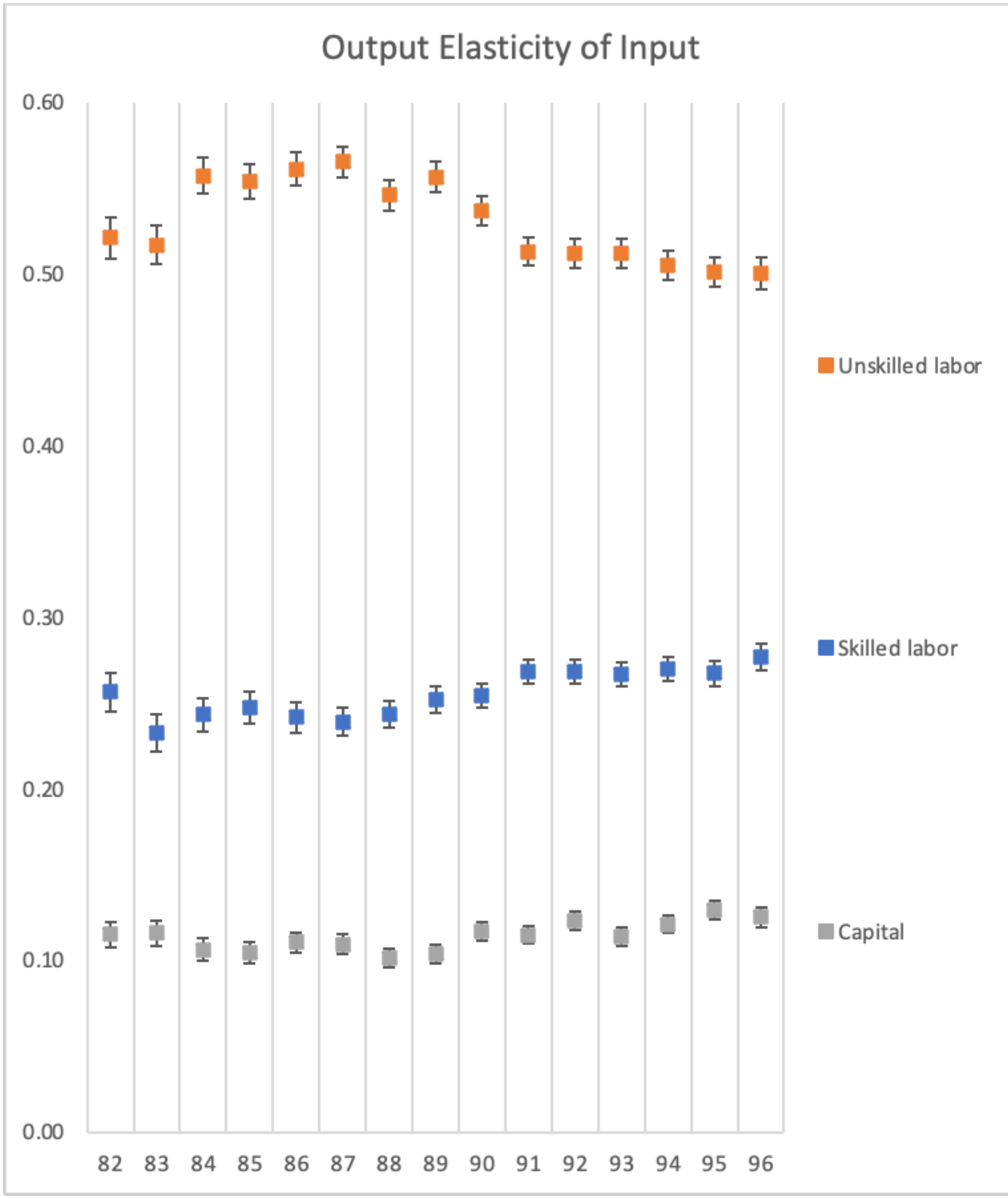
Figure 1.2: Output Elasticity of Inputs[10]



[10] I estimate the output elasticity of skilled workers each year in the MMS dataset between 1982 and 1996.

$$\log(Value - added)_{ijt} = \beta_t \log(Skilled\ labor)_{ijt} + \gamma_t \log(Unskilled\ labor)_{ijt} + \eta_t \log(Capital)_{ijt} + \alpha_j + \delta_t + \varepsilon_{ijt}$$

Figure 1.2: Output Elasticity of Inputs, continued



1.3.3 Closely Linked Industrial Ecosystem in South Korea

The Korean government implemented the *act on the promotion of cooperation between large enterprises and small and medium enterprises* in 1975. According to the act, *chaebol*[11] were encouraged (or guided) to contract intermediate inputs out to Small and Medium Enterprises (SMEs) to build long-term relationships with SMEs. The act aimed at (i) establishing a system of specialization that *chaebol* produces final exporting goods by using intermediate goods supplied by domestic SMEs, and (ii) helping small domestic manufacturing suppliers secure a stable demand market and grow (Lee et al., 2017).

The act promoted cooperation between *chaebol* and SMEs but nevertheless, the relationship between them has been lopsided and *chaebol* have had the initiative (Biggart and Guillen, 1999). The reasons for this are as follows. The Korean government's industrial incentives have focused mainly on *chaebol*. Firms that export goods abroad or invest in machinery had priority in receiving loans with almost zero interest rates and the government protected these exporting firms from import competition by maintaining high import tariffs on the final goods. Taking advantage of this benefit from the government and their own bargaining power, *chaebol* forced their supplier SMEs not to seek other customers - including export markets - and to sell intermediate goods at a lower price (Lee et al., 2017).[12]

The SMEs did not diversify their customers and pursue the export market since (i) they can secure domestic demand from long-term *chaebol* customers, and (ii) their *chaebol* customers would contract fewer intermediate goods from them if they tried to find other customers.

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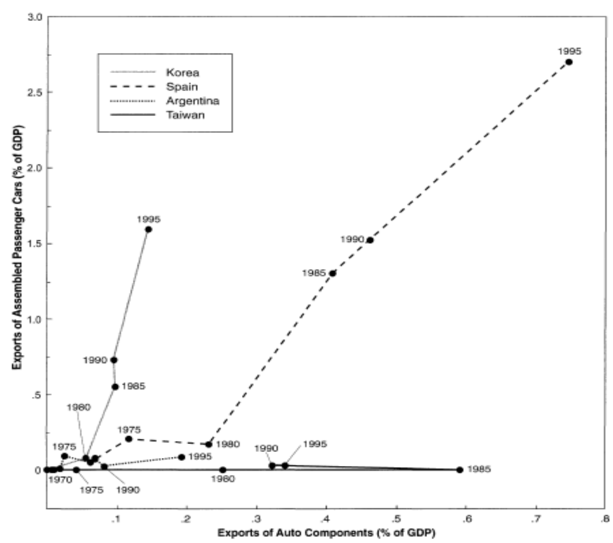
[11] Family controlled big businesses in South Korea, such as Samsung, Hyundai, SK, and LG.

[12] The long-term contracts between *chaebol* and upstream SMEs still exist today: about 90% of survey respondents in the auto/electronics/machinery industry said that they held a long-term contract with their partner firms in 2017 (Lee et al., 2017).

Responding to the price discount request from *chaebol* customers, SMEs focused on expanding volume and decreasing costs rather than on improving the quality of their intermediate goods, (iii) which made it difficult for the firms to achieve the quality standard in the world market. The auto industry in Korea, for example, shows a huge gap in exports per GDP between cars and components, as shown in Figure 1.3 (Biggart and Guillen, 1999). A side effect of this convention, relying on the demand from *chaebol*, was revealed in the Asian Financial Crisis: when the auto assembler Kia went bankrupt, its suppliers followed the assembler to become bankrupt (Biggart and Guillen, 1999).

Figure 1.3: Exports of Assembled Passenger Cars and Automobile Components, 1970 to 1995



Sources: Biggart and Guillen (1999)

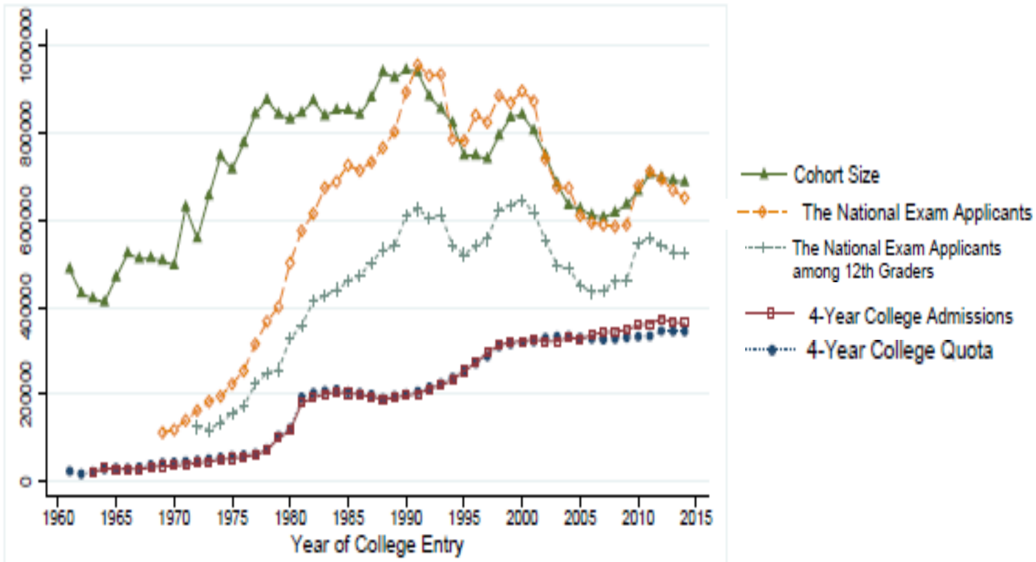
According to the context of South Korea, supplier firms rarely pursued an export market for their intermediate goods, and intermediate goods that the firms produced were supplied to the final *chaebol* partner. These properties match well with the model of complementarity in technology adoption by Buera et al. (2021), and the model of the big push to overcome coordination failure by Sachs and Warner (1999). Since domestic manufacturing firms are closely connected through intermediate goods that supplier firms produce and sell to domestic buyer firms, it is justified to consider the spillover effect and complementarity in technology adoption, i,e., more outside adopters increase a marginal adopter's gain.

1.3.4 The Expansion of the College Enrollment Quota

The Korean government changed its education policy in the early 1980s. The education policy increased the enrollment quota[13] for each major in each college by 30 percent, and also the policy planned to set up a graduation quota limiting the number of students who can finally graduate. In other words, the policy was devised to make it easy to become college students but hard for them to graduate. The government, however, did not implement the planned graduation quota. As a result, the expansion of the enrollment quota (without graduation quota) acted as a catalyst for human capital accumulation in South Korea: the college quota jumped in 1981, and so did the number of college admissions as shown in Figure 1.4 below. The expansion of the enrollment quota and the subsequent increase in the supply of skilled workers to manufacturing industries go well with the theoretical framework in this paper. I assume human capital as an adoption good for a firm to adopt advanced technology. Human capital accumulation in upstream industries, therefore, can be interpreted as more outside adopters. I will verify whether complementarity in technology adoption holds, i.e., more outside adopters increase marginal adopter's gain and whether outside adopters promote a firm's technology shift toward capital-intensity so that the firm can maximize the benefit of the improved intermediate inputs.

[13] The college enrollment quota for each major was determined by the government's educational policy until 1987, when it was liberalized and each private college determined its enrollment quota. The government tended to suppress the college enrollment quota until the late 1970s and favored expanding it after that. The expansion of the college enrollment quota by 30 percent in 1981 is a remarkable event for this change. After 1987, private colleges were allowed to determine their enrollment quota, while the government continued to determine the quota for public colleges. This liberalization led to a further increase in the college enrollment quota (Kim, 2021).

Figure 1.4: Cohort size, college applicants, and college quota in South Korea



Source: Kim (2021)

1.4 Theoretical Framework

The main idea of this chapter is that expansion of the college enrollment quota alleviates the constraint of the supply of skilled workers in upstream industries and that subsequent human capital accumulation in the upstream industries stimulates firms' technology shift toward capital-intensive technology. I connect a model of complementarity in technology adoption from Buera et al. (2021), with a model of simultaneous industrialization, or big push, from Sachs and Warner (1999). I modify the models by introducing skilled labor as adoption goods to discuss the effect of outside human capital accumulation on a firm's technology shift and verify the complementarity in technology adoption.

1.4.1 A model of Complementarity in Technology Adoption and Coordination Failure

Why do most developing countries stick to traditional technology that is unskilled labor-intensive and do not adopt more productive advanced technologies? There have been two major streams of literature to explain this behavior. One asserts there are barriers that prevent firms in developing countries from adopting more productive technology (Parente and Prescott, 1999; Hsieh and Klenow, 2014; Bento and Restuccia, 2017), and the other explains there is coordination failure: a firm does not adopt productive technology because other firms do not adopt (Rosenstein-Rodan, 1943; Murphy et al., 1989). The latter type of failure happens when there is a complementarity in the decision-making process of adopting advanced technology so that it gives more gain to the marginal adopter when there are more adopters. The opposite direction is also valid as well in the situation of coordination failure: fewer adopters lead to less gain for a marginal adopter. A marginal adopter, however, must bear the cost of adopting new technology. Hence, in the initial stage of the development process when the majority uses traditional technology, it is hard to promote firms to adopt more productive modern technology.

I borrow a model from Buera et al. (2021) which shows a chance of complementarity in technology adoption. To consider complementarity in technology adoption in the context of inter-industry relationships, it is useful to include intermediate goods (x) in the production function. Actually, an industry's production process requires a variety of materials, or intermediate goods, made from other industries and/or the industry itself. Suppose there exists a measure one of firms producing a differentiated good $j \in [0,1]$, respectively.

$$y = \frac{A_i}{v_i^{v_i}(1-v_i)^{1-v_i}} l^{1-v_i} x^{v_i} \quad where\ v_i{}^{14} \in [0,1]\ and\ i \in \{t, m\}$$

Modern technology (*m*) is assumed to be more productive,

$$\frac{A_m}{v_m^{v_m}(1-v_m)^{1-v_m}} > \frac{A_t}{v_t^{v_t}(1-v_t)^{1-v_t}}$$

And is more intermediate goods-intensive than the traditional technology (*t*) which is unskilled labor-intensive.

$$v_m > v_t$$

Adopting modern technology requires an adoption cost of hiring skilled workers. These adoption goods enable the adopting firm to depend less on unskilled workers and to improve the productivity of intermediate goods.

The differentiated goods are combined into an intermediate aggregate,

$$X = \left[\int y_j^{\frac{\eta-1}{\eta}} dj\right]^{\frac{\eta}{\eta-1}}$$

Where η, the elasticity of substitution, is assumed to be greater than 1.

---

[14] v_i indicates intermediate input-elasticity.

Then the demand for the differentiated good *j* is

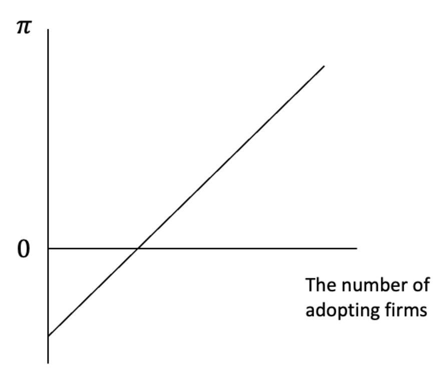
$$y_j = \left(\frac{P}{p_j}\right)^{\eta} X$$

where *P*, the price index of the intermediate aggregate is

$$P = \left[\int p_j^{1-\eta} dj\right]^{\frac{1}{1-\eta}}$$

In this model, an increase in the number of adopting firms decreases the aggregate price (*P*), since modern technology is more productive. It leads to a pressure to decrease the price of output produced by the marginal adopting firm, and hence, the firm's profit will decrease: This is called the competition effect. The decrease of aggregate price (*P*), however, (1) increases the demand for the intermediate goods the marginal adopter produces,[15] and (2) decreases the cost of intermediate goods the marginal adopter uses for production. These changes will increase the firm's profit. If the latter two factors outweigh the competition effect, then there is a complementarity in the firm's technology adoption decision, and the marginal adopting firm's profit is increasing in the number of adopters as shown in Figure 1.5.

Figure 1.5: A marginal adopter's profit is increasing in the number of adopting firms



Source: Sachs and Warner (1999)

[15] Since the demand for intermediate aggregate increases.

Coordination failure exists when there is a complementarity in firms' decision on adopting modern technology. In other words, if more adopting firms lead to more benefit for the marginal adopter, then there can be multiple equilibria and coordination failure can happen. In Figure 1.5 above, it can be seen that the marginal adopter's payoff is negative if there are not enough adopters in the upstream industries. It will discourage a potential adopter who must pay an adoption cost when it adopts modern technology, but expects a small benefit. A Big Push theory plays a role in explaining how to overcome this coordination failure problem.

1.4.2 A model of Big Push to overcome Coordination Failure

I borrow a model from Sachs and Warner (1999) which shows a clue to overcoming the coordination failure in the situation of complementarity in technology adoption. Suppose each firm considers the *present value of future profits* with an *optimistic or pessimistic* view instead of considering the profit earned at the time of adopting modern technology. A firm maximizes the *present value of future profits* and chooses whether to adopt modern technology or not.

A firm with *an optimistic view* expects the number of adopting firms (n) to increase (from the initial number of adopters at t_0, $n(t_0)$, to the final number of adopters at T, $n(T) = N$). Hence, the present value of future profits with an optimistic view denoted $V^o\big(n(t_0)\big)$ is the discounted sum of profits from the initial number of adopters at time t_0, $n(t_0)$, to the number of entire intermediate goods producers (N) at time T where the discount rate is ρ.

$$V^o\big(n(t_0)\big) = \int_{t_0}^{T} e^{-\rho(t-t_0)}\pi(n(t))dt$$

Optimistic equilibria thus lie in any given number of adopting firms when (i) firms have an optimistic view and (ii) the corresponding present value of future profits is positive. Under these conditions, self-fulfilling full industrialization, or full adoption of modern technology, can be achieved. The pessimistic view expects that the number of adopting firms (n) is decreasing (from $n(t_0)$ to $n(T) = 0$). The present value of future profits with a pessimistic view denoted $V^p(n(t_0))$ is the discounted sum of profits from the initial number of shifters $n(t_0)$ $at\ time\ t_0$ to zero adopters at time *T*.

$$V^p(n(t_0)) = \int_{t_0}^{T} e^{-\rho(t-t_0)}\pi(n(t))dt$$

Therefore, pessimistic equilibria lie in any given number of adopting firms when firms have a pessimistic view and the corresponding present value of future profits is negative hence self-fulfilling de-industrialization, or staying with traditional technology, can happen.

There exists some range of the number of adopting firms in which both optimistic and pessimistic equilibria overlap, as shown in Figure 1.6a. In this case, whether full industrialization or de-industrialization occurs depends on which type of expectation is dominant. The economy can achieve a big push, or simultaneous industrialization/technology shift, in that range. However, in the region of only optimistic equilibria, full industrialization will happen. In the region of only pessimistic equilibria, on the other hand, de-industrialization will happen.

Suppose not every firm but only n' $(< N)$ firms can hire $\bar{s}$ units of skilled workers needed to adopt modern technology, respectively, before the educational policy reform. The expansion of the college enrollment quota (i) alleviates the constraint of the supply of skilled workers which will lead to the increase in the number of potential adopting firms and the following expansion of the profit line, and (ii) decreases the skill premium that leads to the upward shift of the profit line. The value functions with both an optimistic view, denoted V^o, and a pessimistic view, denoted V^p, shift inward due to the change of the profit line. As a result, the educational policy reform shrinks the "only pessimistic equilibria," area, as shown in Figure 1.6b. This result shows that the chance of being stuck in the undesirable equilibrium can decrease after the expansion of the college enrollment quota. Furthermore, (iii) the educational policy reform makes a firm expect other firms will have more chance to adopt modern technology since the reform increases the college enrollment quota of every major by 30% which is huge by amount and industry-wide by range. As a result, a marginal decision-making firm will become more optimistic and less pessimistic. Iteration of this process will increase more and more adopters in the industries and a firm that buys intermediate goods from these industries will adopt modern technology and the country will settle into a desirable equilibrium. Hence, the expansion of the college enrollment quota enables the country to have a higher chance of overcoming coordination failure and achieving full industrialization, or full adoption of modern technology.

Figure 1.6a: Optimistic and Pessimistic Value Function

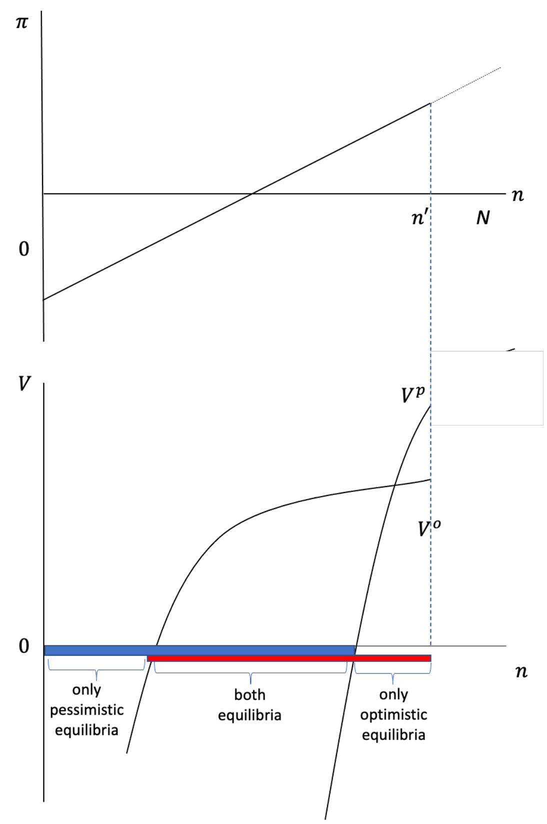
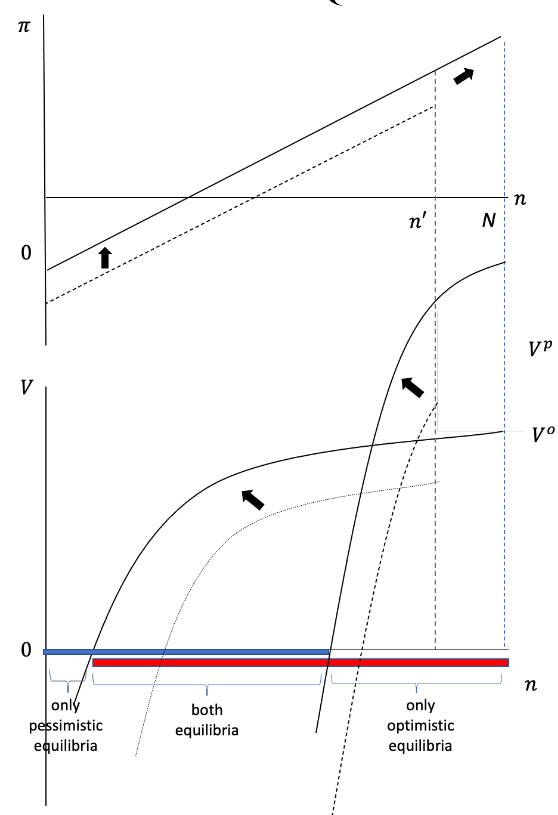


Figure 1.6b: Effect of the Expansion of the Enrollment Quota



Source: Sachs and Warner (1999)

1.5 Data

The key idea in this paper is that the expansion of the college enrollment quota since the early 1980s has effects similar to those of a big push and alleviates the supply constraint of skilled workers in industries that supply intermediate inputs to other industries. It solves prisoner's dilemma-like situation of coordination failure in firms' technology adoption. If there is to be more human capital accumulation in the upstream industries, then the intermediate inputs that a firm buys from those industries will be cheaper, so the firm using these inputs wants to maximize the benefit by adopting intermediate input-intensive modern technology. To examine this process, i.e. complementarity in technology adoption, I need two types of data: (i) an industry panel that contains both development outcomes and human capital accumulation, and (ii) an Input-Output (IO) table for the spillover effect from upstream industries.

First, I use the Mining and Manufacturing Survey[16] (MMS) to get an industry panel between 1982 and 1996. It is plant-level data made by Statistics Korea and it contains outcomes such as production, value-added, investment, etc. Also, it contains the number of employees for both blue-collar (unskilled) and white-collar (skilled) workers in each plant. I choose 1982 as the start year since I focused on the post-industrial policy era, and 1982 data is the earliest year for which data are available. I use 1996 as the terminal year to avoid confusion with the effects of the Asian Financial Crisis in 1997. Due to several changes in the Korean Standard Industry Code (KSIC), the industry codes applied to the 1982-1996 dataset are not based on the same standard. To be specific, the data from 1990-1996 are based on the 6th KSIC, the 1983-1989 data are based on the 5th KSIC, and the data in the initial year are based on the 4th KSIC. Hence, I harmonize the

[16] MMS data can be accessed only remotely and cannot be carried out. Graphs and tables generated from the data have to be reviewed by the Statistics Korea before they can be downloaded. The review takes 5 to7 business days.

dataset by setting the 6th KSIC as a standard code for the entire 1982-1996 period and altering the industry codes used in the 1980s to the corresponding ones in the 6th KSIC. To get the real values of capital and investment, I calculated deflators from Gross Capital Formation by the Type of Capital Goods made by the Bank of Korea (BOK). The BOK data show both the current and 2015-year prices of each type of gross capital formation, i.e., building and structure, machinery and equipment, and vehicles, in each year. Thus, I got deflators of each type of capital by dividing the current price by the 2015-year price. To get a real value of output and value-added, I used the industry-level Producer Price Index (PPI) each year from BOK. Since the categories of industry used in PPI are different from the ones used in MMS, I harmonized both datasets to match PPI in each industry in MMS.

Second, I use the 1980 IO table to get a measure of the spillover effect of human capital accumulation from upstream industries. I use the input coefficients[17] as weights[18] to construct a spillover variable that is a weighted sum of skill ratios in the upstream industries. I assume patterns of trade among domestic industries are the same as the ones in 1980. To get a congruent panel dataset, I harmonized the category of industries used in the MMS and IO table so that each industry in MMS has a spillover variable. IO tables have 396 basic sectors over the whole industries, of which, 256 sectors are manufacturing industries. I digitized[19] the 396x396 IO matrix table from the BOK-published book in 1980. The harmonized MMS has 585 5-digit industries based on the 6th KSIC and re-harmonized the MMS and IO tables by assigning the corresponding manufacturing sectors in the IO table to each 5-digit MMS industry.

[17] A portion of intermediate input bought from each supplier industry.

[18] If an industry A buys intermediate goods more from an industry B than an industry C, then A will be more affected by human capital accumulation in B than in C.

[19] It takes about 100 hours for me to make a 396 x 396 IO matrix manually.

Table 1.1: Descriptive Statistics

	[1982-1996]	1982	1983	1984	1985	1986	1987	1988
# Firms	979,949	36,709	39,129	41,450	43,930	49,956	54,248	59,800
Skilled labor	9.6788	10.0555	10.4519	10.5640	10.6642	10.7044	11.0958	11.045
	(80.5576)	(61.2131)	(71.4057)	(70.6458)	(79.8180)	(84.4091)	(74.3075)	(80.9635)
Unskilled labor	32.0373	46.13	46.0270	45.1707	43.9177	44.2041	44.2102	40.5143
	(196.9925)	(264.577)	(258.9279)	(246.9508)	(243.1571)	(240.2407)	(244.3873)	(227.867)
Capital	1736.711	1205.034	1215.868	1317.291	1315.8	1290.305	1440.825	1498.515
	(32538.57)	(29830.56)	(28439.87)	(25918.6)	(22054.97)	(20625.88)	(22980.41)	(26109.62)
Skill ratio[20]	0.3079	0.2306	0.2372	0.2410	0.2494	0.2509	0.2628	0.2805
	(0.6918)	(0.4049)	(0.4291)	(0.4192)	(0.4652)	(0.4739)	(0.4819)	(0.4974)
Forward[21]	0.2250	0.1767	0.1840	0.1916	0.2016	0.1946	0.1994	0.2080
	(0.0811)	(0.0734)	(0.0802)	(0.0786)	(0.0812)	(0.0795)	(0.0751)	(0.0779)
Investment	390.2933	233.7413	180.6859	257.9084	242.213	294.6064	396.5139	357.931
	(12319.43)	(9003.869)	(4007.955)	(4552.391)	(3607.695)	(5954.941)	(14878.75)	(6895.069)
Profit	1680.024	921.1787	1006.96	1083.769	1133.992	1174.213	1269.854	1364.729
	(31655.27)	(15305.82)	(15116.99)	(16028.27)	(16985.1)	(17204.76)	(17798.68)	(22200.86)
Price	87.1174	78.6626	77.2739	78.0467	78.4610	82.1406	87.5422	94.9960
	(237.8736)	(324.9534)	(306.4587)	(297.6966)	(288.0478)	(289.9771)	(305.4828)	(342.3792)
Industry-level controls								
Capital-Production ratio	0.5360	0.6057	0.5464	0.5653	0.6258	0.5572	0.5866	0.6341
	(1.9800)	(2.9728)	(1.8270)	(2.0781)	(2.6980)	(2.5941)	(2.5852)	(2.9941)
Labor-Production ratio	0.0255	0.0601	0.0523	0.0452	0.0441	0.0396	0.0363	0.0332
	(0.0906)	(0.2392)	(0.1817)	(0.1439)	(0.1384)	(0.1099)	(0.1045)	(0.1000)
Value added-Production ratio	0.4407	0.3977	0.4162	0.4047	0.4116	0.4039	0.4008	0.4105
	(0.0913)	(0.1013)	(0.0983)	(0.0902)	(0.0914)	(0.0841)	(0.0861)	(0.0877)
Profit-Production ratio	0.3356	0.3099	0.3245	0.3156	0.3218	0.3169	0.3157	0.3257
	(0.1566)	(0.1383)	(0.1421)	(0.1299)	(0.1343)	(0.1301)	(0.1313)	(0.1262)
Profit-Sales ratio	0.2784	0.2852	0.3198	0.3264	0.2554	0.3260	0.3226	0.3402
	(0.8075)	(0.4679)	(0.3445)	(0.1929)	(0.9914)	(0.2063)	(0.2203)	(0.1656)

[20] $Skill\ ratio = \left(\frac{Skilled}{Unskilled}\right)_{ijt}$

[21] $Forward = \sum_j \alpha_{ji} \left(\frac{Skilled}{Unskilled}\right)_{it}$

Table 1.1: Descriptive Statistics, continued

	1989	1990	1991	1992	1993	1994	1995	1996
# Firms	65,548	68,705	72,245	74,700	88,870	91,373	96,181	97,105
Skilled labor	10.4877	10.3288	10.0792	9.5043	8.5614	8.5337	8.5015	8.3376
	(77.2388)	(76.9048)	(80.2238)	(71.9604)	(77.7689)	(83.1221)	(83.8222)	(101.1473)
Unskilled labor	35.7631	32.9745	29.5859	27.1129	23.2315	22.8651	21.6443	21.2298
	(197.2498)	(195.0813)	(180.6464)	(166.5952)	(145.6833)	(152.1385)	(153.806)	(161.1709)
Capital	1583.836	1757.647	1799.053	2001.048	1883.365	1973.628	2039.884	2239.884
	(28508.18)	(40050.78)	(33222.05)	(39509.27)	(35036.11)	(34098.96)	(34900.68)	(38097.04)
Skill ratio	0.2925	0.3221	0.3365	0.3491	0.3412	0.3395	0.3460	0.3386
	(0.5732)	(0.5981)	(0.6558)	(0.7145)	(0.7215)	(0.7016)	(0.9110)	(1.0710)
Forward	0.2155	0.2331	0.2377	0.2385	0.2383	0.2431	0.2471	0.2547
	(0.0724)	(0.0803)	(0.0803)	(0.0773)	(0.0755)	(0.0783)	(0.0734)	(0.0814)
Investment	390.928	440.0516	522.3687	508.4065	338.5866	350.9078	477.8409	496.0289
	(8918.865)	(17705.85)	(19912.55)	(17319.35)	(6868.678)	(7756.702)	(14626.89)	(13982.45)
Profit	1367.51	1663.433	1848.265	1998.955	1848.008	2029.873	2168.483	2308.604
	(22756.04)	(32164.58)	(33548.81)	(34619.06)	(34093.2)	(38589.18)	(45564.33)	(41167.62)
Price	92.0945	88.2571	86.7541	86.7367	87.7200	90.1870	90.8812	88.7682
	(290.8022)	(234.8656)	(181.1223)	(167.5399)	(172.9268)	(186.2534)	(173.9154)	(134.2094)
Industry-level controls								
Capital-Production ratio	0.6426	0.5983	0.5246	0.5357	0.5053	0.4766	0.4448	0.4203
	(2.6773)	(2.4761)	(1.6278)	(1.4399)	(1.2571)	(1.0890)	(1.0318)	(0.7852)
Labor-Production ratio	0.0295	0.0237	0.0194	0.0172	0.0154	0.0138	0.0117	0.0103
	(0.0823)	(0.0565)	(0.0355)	(0.0284)	(0.0244)	(0.0224)	(0.0169)	(0.0122)
Value added-Production ratio	0.4159	0.4417	0.4578	0.4646	0.4692	0.4688	0.4617	0.4672
	(0.0836)	(0.0887)	(0.0877)	(0.0823)	(0.0874)	(0.0870)	(0.0831)	(0.0815)
Profit-Production ratio	0.3253	0.3417	0.3493	0.3546	0.3510	0.3455	0.3358	0.3458
	(0.1239)	(0.1386)	(0.1323)	(0.1592)	(0.1775)	(0.1838)	(0.1910)	(0.1824)
Profit-Sales ratio	0.3432	0.3484	0.3610	0.3527	0.2880	0.2378	0.0760	0.1795
	(0.2045)	(0.2535)	(0.2756)	(0.2825)	(0.6290)	(0.8187)	(1.7634)	(1.2590)

1.6 Specification

This paper emphasizes complementarity in technology adoption: the marginal adopter gains more when there are more adopters outside. I assume that skilled labor serves as an adoption good for modern technology which is less unskilled labor-intensive and more intermediate input-intensive. Skilled labor enables a firm to adopt advanced machinery and equipment that helps the firm produce more output from intermediate input and depend less on unskilled labor. By considering intermediate inputs in the production process, I can verify the role of the expansion of the college enrollment quota in the technology shift in manufacturing industries. The expansion of the college enrollment quota in the early 1980s led to an increase in the supply of skilled workers in the manufacturing industries. As there are more chances to increase the number of adopters (firms that hire skilled workers) in the industries that supply intermediate inputs, the marginal adopter who hires skilled workers and adopts modern technology would get more benefit from intermediate inputs that become cheaper in price.[22] As a result, the firm that is in the decision-making process is more likely to adopt modern technology under the circumstances that complementarity in technology adoption holds and a Big Push-type policy is implemented (e.g. the expansion of the college enrollment quota) .

1.6.1 Complementarity in Technology Adoption

To examine whether complementarity in technology adoption holds, or whether more adopters increase a marginal adopter's gain, I estimate a series of fixed effect model

[22] Since modern technology is more intermediate input-intensive.

$$(1.1)\ Outcome_{ijt} = \beta_0 + \beta_S(Skill\ ratio)_{ijt} + \beta_F(Forward)_{it}$$

$$+\beta_{SF}(Skill\ ratio)_{ijt}(Forward)_{it} + \mathrm{W}_{it}^{'}\Gamma + \alpha_j + \delta_t + \varepsilon_{ijt}$$

where $Outcome_{ijt}$ is either a firm's investment, profit, or price, and $Skill\ ratio_{ijt}$ is the ratio of skilled-to-unskilled labor (hereafter *skillratio*) in firm *j* in industry *i* in time *t*. $Forward_{it}$ is the weighted sum of skilled-to-unskilled ratios (hereafter *forward*) in *i*'s upstream industries *k* in time *t* with input coefficients[23] in 1980 I-O table as weights.[24] The vector W_{it} indicates a set of industry characteristics of average productivity ($\frac{Production}{Captial}, \frac{Production}{Labor^{25}}, \frac{Value-added}{Production}$), profitability ($\frac{Profit}{Production}, \frac{Profit}{Sales}$), and trade[26] ($\sum_{t=1982}^{1996}\left(\frac{exports}{total\ supply}\right)_{i1980} * Year_t$, $\sum_{t=1982}^{1996}\left(\frac{imports}{total\ supply}\right)_{i1980} * Year_t$). I also adopt firm- ($\alpha_j$) and time-fixed effects (δ_t) to eliminate firm-specific characteristics over time and year-specific properties across firms. An error term ε_{ijt} refers to unobserved characteristics that affect a firm's $Outcome_{ijt}$. Standard errors are clustered at a firm level and robust to heteroskedasticity.

Control variables W_{it} and *forward* are industry-level variables, and thus they are exogenous to the firm. A firm's *skillratio*, however, could bring endogeneity issues: a firm's unobserved characteristics in the error term, ε_{ijt}, could affect both *skillratio* and $Outcome_{ijt}$, and there could be reverse causality between them as well. To address the problem of endogeneity in the variable of *skillratio*, I adopt the one- and two-year lagged *skillratios* as instrumental variables. It

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[23] A weighted sum of skill ratio in industries *k* selling their products to the industry i (where the firm j belongs) with input coefficients ($\alpha_{ki} = \frac{x_{ki}}{\sum_{k'} x_{k'i}}$) as weights.

[24] $Forward_{it} = \sum_k \alpha_{ki}(Skill\ ratio)_{kt}$

[25] Labor is a sum of skilled and unskilled labor.

[26] Exports, imports, and total supply (=total output + imports) come from 1980 I-O table. The ratio of exports-to-total supply and imports-to-total supply are interacted with year dummies.

is unlikely that there exist shocks (or confounders) that are effective for more than one year and affect both lagged *skillratios* and the current outcome variables. If it is the case, the instrumental variables are arguably *exogenous* to a confounder in the current error term. Furthermore, instruments of one- and two-year lagged *skillratios* are likely to be *relevant* to an endogenous regressor of current *skillratio*. First stage regressions are given by

(1.2) $$(Skill\ ratio)_{ijt} = b_0 + Z_{ijt-2}^{t-1} b_s + Z_{ijt-2}^{t-1} (Forward)_{it} b_{sf}$$

$$+ b_f (Forward)_{it} + \mathrm{W}_{it}^{'} \mathrm{c} + a_j + d_t + e_{ijt}$$

$$(Skill\ ratio)_{ijt} (Forward)_{it} = b_{1,0} + Z_{ijt-2}^{t-1} b_{1,s} + Z_{ijt-2}^{t-1} (Forward)_{it} b_{1,sf}$$

$$+ b_{1,f} (Forward)_{it} + \mathrm{W}_{it}^{'} \mathrm{c}_1 + a_{1,j} + d_{1,t} + e_{1,ijt}$$

where Z_{ijt-2}^{t-1} is a vector of one- and two-year lagged *skillratios*. Other notation is the same as in Equation (1.1).

The parameter of interest in the Equation (1.1) is β_{SF}, which is the coefficient on the interaction *skillratio * forward*. It verifies whether there exists complementarity in technology adoption. The theoretical framework predicts a decrease in the price of the intermediate aggregate when there is an increase in human capital accumulation (there is more adopters) in the upstream industries. It decreases a firm's price of its product and so it reduces the firm's profit. This is called competition effect. However, a decrease in the price of intermediate aggregate raises the demand for the firm's product, and also decreases the cost of intermediate inputs the firm uses to produce its product. These two effects increase the firm's profit. If the latter two effects are larger than the competition effect, so that more adopters in upstream industries increase a firm's profit, then the firm hires skilled labor and adopts intermediate input-intensive modern technology to take advantage of cheaper intermediate inputs. As a result, more outside adopters increase the marginal adopter's gain, and so complementarity in technology adoption holds. According to the theoretical framework, therefore, a coefficient on interaction variable, β_{SF}, will be negative when $Outcome_{ijt}$ is price, and it will be positive when $Outcome_{ijt}$ is profit or investment.

Table 1.2 presents the results from estimating a series of Equation (1.1) when $Outcome_{ijt}$ is profit. Each columns show that a coefficient on the interaction variable, β_{SF}, is positive and adding industry-level control variables of average productivity, profitability, and trade do not change the direction. The results indicate that complementarity in technology adoption holds: the more firms hire skilled labor and adopt modern technology, the better it is for a firm to do it. The coefficient on *skillratio*, β_S, represents marginal adopter's profit when there are no adopters in the upstream industries. The estimate of this coefficient is negative in every model. When there are no adopters in upstream industries, the marginal adopter cannot get the benefit of lowered price of intermediate aggregate nor increased demand for the product the marginal adopter produced. The marginal adopter has a chance of incurring a loss since hiring skilled labor involves a fixed cost. Hence, the marginal adopter's profit is initially negative when there are no adopters in the upstream industries, and the profit will turn positive beyond the break-even *forward* ratio since complementarity in technology adoption holds ($\beta_{SF} > 0$). The break-even *forward* ratios are between 0.2106 and 0.3614.[27]

[27] Mean value and standard deviation of *forward* are 0.2250 and 0.0811, respectively.

Table 1.2: Complementarity: profit, skilled-to-unskilled ratio

Profit	(1) FE	(2) FE+IV	(3) FE	(4) FE+IV	(5) FE	(6) FE+IV	(7) FE	(8) FE+IV
skillratio	-254*	-3919	-249*	-1009	-249*	-1056	-295*	-3173
	(138)	(4611)	(148)	(4006)	(146)	(3996)	(157)	(4907)
forward	-5665***	-13044**	8186*	6305	8183*	6298	7568**	3528
	(1920)	(5209)	(4273)	(4662)	(4210)	(4717)	(3690)	(3967)
skillratio	1206***	11181	1139**	3449	1141**	3576	1305***	8779
* *forward*	(440)	(10406)	(460)	(8952)	(458)	(8944)	(486)	(11105)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry-level Controls								
Productivity	N	N	Y	Y	Y	Y	Y	Y
Profitability	N	N	N	N	Y	Y	Y	Y
Trades	N	N	N	N	N	N	Y	Y
Observations	959564	485537	959562	485537	959514	485512	949164	478041
Outcome Mean	1704	2697	1704	2697	1704	2697	1707	2712
K-P p-value	-	0.0524	-	0.0526	-	0.0529	-	0.0796
Hansen J p-value	-	0.1216	-	0.0267	-	0.0261	-	0.0888
Break-even Forward ratio	0.2106	0.3505	0.2186	0.2925	0.2182	0.2953	0.2261	0.3614

Notes. Estimates are based on the model in Equation (1.1), using firm-year observations over the period 1982-1996. The dependent variable is profit of a firm in a given year. *skillratio* indicates the ratio of skilled-to-unskilled labor and *forward* indicates the weighted sum of the ratio of skilled-to-unskilled labor in the upstream industries with input coefficients as weights. I apply two-stage least square (IV) method in column (2), (4), (6), and (8) using Equation (1.2) as first-stage regression. Controls for productivity include industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include industry-level ratios of profit-to-production, and profit-to-sales. Controls for trade include exports-to-total supply ratios and imports-to-total supply ratios in 1980 I-O table interacted with year dummies. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 1.3 is the results of estimating variants of Equation (1.1) when investment is used in $Outcome_{ijt}$. Each column shows that the coefficient on the interaction variable, β_{SF}, is positive and stable after controlling industry-level characteristics of productivity, profitability and trade. The results indicate that the marginal adopter invests more when there are more adopters in the upstream industries since complementarity in technology adoption holds and more adopters increase the marginal adopter's gain. The break-even *forward* ratios are between 0.2268 and 0.3188.

Table 1.3: Complementarity: investment, skilled-to-unskilled ratio

Investment	(1) FE	(2) FE+IV	(3) FE	(4) FE+IV	(5) FE	(6) FE+IV	(7) FE	(8) FE+IV
skillratio	-26	-1035	-22	-809	-23	-827	-31	-1297
	(53)	(1428)	(52)	(1364)	(53)	(1374)	(56)	(1729)
forward	1262	-400	1808*	720	1815*	714	1477*	-193
	(835)	(1368)	(993)	(1400)	(994)	(1403)	(867)	(1416)
skillratio * *forward*	110	3472	97	2911	100	2959	122	4068
	(180)	(3373)	(177)	(3212)	(178)	(3238)	(187)	(4073)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry-level Controls								
Productivity	N	N	Y	Y	Y	Y	Y	Y
Profitability	N	N	N	N	Y	Y	Y	Y
Trade	N	N	N	N	N	N	Y	Y
Observations	959564	485537	959562	485537	959514	485512	949164	478041
Outcome Mean	397	521	397	521	397	521	399	525
K-P p-value	-	0.0524	-	0.0526	-	0.0529	-	0.0796
Hansen J p-value	-	0.2735	-	0.2497	-	0.2511	-	0.2961
Break-even Forward ratio	0.2364	0.2981	0.2268	0.2779	0.2300	0.2795	0.2541	0.3188

Notes. Estimates are based on the model in Equation (1.1), using firm-year observations over the period 1982-1996. The dependent variable is investment of a firm in a given year. *skillratio* indicates the ratio of skilled-to-unskilled labor and *forward* indicates the weighted sum of the ratio of skilled-to-unskilled labor in the upstream industries with input coefficients as weights. I apply two-stage least square (IV) method in column (2), (4), (6), and (8) using Equation (1.2) as first-stage regression. Controls for productivity include industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include industry-level ratios of profit-to-production, and profit-to-sales. Controls for trade include exports-to-total supply ratios and imports-to-total supply ratios in 1980 I-O table interacted with year dummies. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 1.4 presents the results from estimating variants of Equation (1.1) when $Outcome_{ijt}$ is price. Fixed effect (FE) regressions, column (1), (3), (5), and (7), show negative coefficient on the interaction variable regardless of control variables for industry-level characteristics of average productivity, profitability, and trade. When it comes to instrumental variable (IV) regressions, column (2), (4), (6), and (8), a negative coefficient on the interaction variable shows up when all industry-level characteristics are included in the regression (column (8)). The results support the theoretical prediction: more adopters in the upstream industries decrease the price of aggregate intermediate as well as the price of product a firm produces. The break-even *forward* ratios are between 0.3242 and 0.4980.

Table 1.4: Complementarity: price, firm-level regression, skilled-to-unskilled ratio

Price	(1) FE	(2) FE+IV	(3) FE	(4) FE+IV	(5) FE	(6) FE+IV	(7) FE	(8) FE+IV
skillratio	0.1639 (0.3274)	-2.0872 (10.5183)	0.1274 (0.3296)	-2.3314 (10.6434)	0.1825 (0.3305)	-1.5126 (10.5757)	1.2110*** (0.4005)	27.0555 (21.8628)
forward	-99.9969*** (8.2194)	-92.9611*** (13.5801)	-95.6843*** (8.0380)	-90.6408*** (13.7618)	-96.1628*** (8.0862)	-90.3392*** (13.6972)	-67.1358*** (5.0167)	-41.7897** (16.9651)
skillratio * *forward*	-0.3696 (0.9475)	4.4944 (24.0188)	-0.2558 (0.9568)	5.2074 (24.3131)	-0.4570 (0.9632)	3.0179 (24.1789)	-3.7359*** (1.1875)	-65.1688 (50.2014)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry-level Controls								
Productivity	N	N	Y	Y	Y	Y	Y	Y
Profitability	N	N	N	N	Y	Y	Y	Y
Trade	N	N	N	N	N	N	Y	Y
Observations	959564	485537	959562	485537	959514	485512	949164	478041
Outcome Mean	87.6588	83.6599	87.6589	83.6599	87.6613	83.6623	87.9570	83.9947
K-P p-value	-	0.0524	-	0.0526	-	0.0529	-	0.0796
Hansen J p-value	-	0.1295	-	0.1150	-	0.1189	-	0.9200
Break-even Forward ratio	0.4435	-	0.4980	-	0.3993	-	0.3242	0.4152

Notes. Estimates are based on the model in Equation (1.1), using firm-year observations over the period 1982-1996. The dependent variable is price of a firm in a given year. *skillratio* indicates the ratio of skilled-to-unskilled labor and *forward* indicates the weighted sum of the ratio of skilled-to-unskilled labor in the upstream industries with input coefficients as weights. I apply two-stage least square (IV) method in column (2), (4), (6), and (8) using Equation (1.2) as first-stage regression. Controls for productivity include industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include industry-level ratios of profit-to-production, and profit-to-sales. Controls for trade include exports-to-total supply ratios and imports-to-total supply ratios in 1980 I-O table interacted with year dummies. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

1.6.2 Human Capital Accumulation in the Upstream Industries and Technology Shift

To examine whether more adopters in the upstream industries cause a marginal adopter's technological shift toward capital-intensive production technique, I construct a model by taking a log on Cobb-Douglas production function and interacting logged inputs with a spillover variable of human capital accumulation outside a firm. I use two types of spillover variables with different coverage. One is the ratio of skilled-to-unskilled labor in the industry to which a firm belongs, $Skill\ ratio_{it}$. This type of spillover variable considers that a large proportion of intermediate inputs a firm procures is usually from the industry to which the firm belongs. The other is a weighted sum of the ratio of skilled-to-unskilled labor in the upstream industries, *forward*. I estimate the model[28]

(1.3) $Y_{ijt} = X'_{ijt}\beta + (Spillover)_{it}X'_{ijt}\gamma + \alpha_j + \delta_t + \varepsilon_{ijt}$

where Y_{ijt} is a log of output (production or value-added)[29] and X_{ijt} is a set of logged inputs (intermediate inputs, skilled labor, unskilled labor, and capital) in firm *j* in industry *i* in time *t*. A variable of $Spillover_{it}$ is either $Skill\ ratio_{it}$ or *forward*. The variables α_j and δ_t represent firm- and year-fixed effect respectively to get rid of firm-specific characteristics over time and year-specific properties across entities. The error term ε_{ijt} refers to unobservable characteristics. Standard errors are clustered at a firm level.

In Equation (1.3), there could be a confounder of unobserved productivity shock in the error term and it could be correlated with both (logged) inputs and value-added. I use the Levinsohn-

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[28] Akerman et al. (2015) use the same approach to examine the effect of broadband adoption on the productivity of each production input.

[29] Plant-level value-added data is available in MMS dataset. It is the value of production minus intermediate inputs used for production.

Petrin[30] (LP) method to address this endogeneity problem in the identification of the Cobb-Douglas production function. See Appendix A.6 for more details about applying LP method in Equation (1.3).

Table 1.5 and 1.6 presents the results from estimating variants of Equation (1.3). All columns in Table 1.5 use $Skill\ ratio_{it}$ as a spillover variable to interact with X_{ijt} while all columns in Table 1.6 use *forward* as a spillover variable. In each table, Column (1) uses intermediate inputs and unskilled labor as inputs for production. It is a baseline regression as shown in the theoretical framework. Column (2) adds skilled labor and capital as inputs for production. The result will show whether intermediate input-intensive technology is also skilled labor- and capital-intensive. Column (3) gets rid of intermediate inputs by considering unskilled labor, skilled labor, and capital as inputs for value-added.

All columns in Table 1.5 and 1.6 show positive coefficients on intermediate inputs, skilled labor, and capital (except column (2) in Table 1.5) that are interacted with spillover variables and negative coefficients on unskilled labor interacted with spillover variables. These results are consistent with the prediction that human capital accumulation in the upstream industries will increase a firm's output elasticity of intermediate inputs, and also that of capital and skilled labor, but decrease that of unskilled labor. The results provide empirical evidence that human capital accumulation in upstream industries promotes a firm's technology shift toward capital- and skilled labor-intensive production technique in South Korea between 1982 and 1996. To be specific, a one standard deviation increase in the human capital spillover increases capital

[30] Levinsohn-Petrin (2003) use intermediate inputs as proxies for unobserved productivity shock. Their method resolves the problem of zero-investment in nontrivial number of firms in Olley-Pakes (1996) that use investment as a proxy.

productivity by 2.47 percent when $Skill\ ratio_{it}$ is used for spillover variable, and by 3.06 to 4.41 percent when *forward* is used for spillover variable, from the initial level of capital productivity with zero spillover.

Table 1.5: Technology Shift, $Skill\ ratio_{it}$

	D.V.= *Log (Production)*		D.V.= *Log (Value-added)*
	(1)	(2)	(3)
	FE	FE	FE
Log (Intermediate)	0.4823***	0.4924***	
	(0.0017)	(0.0024)	
Log (Unskilled)	0.3939***	0.2992***	0.5682***
	(0.0028)	(0.0029)	(0.0042)
Log (Skilled)		0.1161***	0.2370***
		(0.0022)	(0.0034)
Log (Capital)		0.0474***	0.1098***
		(0.0015)	(0.0022)
Log (Intermediate) * $Skill\ ratio_{it}$	0.0817***	0.0857***	
	(0.0042)	(0.0058)	
Log (Unskilled) * $Skill\ ratio_{it}$	-0.1309***	-0.1041***	-0.1112***
	(0.0070)	(0.0068)	(0.0100)
Log (Skilled) * $Skill\ ratio_{it}$		0.0003	0.0569***
		(0.0052)	(0.0085)
Log (Capital) * $Skill\ ratio_{it}$		-0.0155***	0.0110***
		(0.0039)	(0.0054)
$Skill\ ratio_{it}$	-0.0922***	-0.1779***	0.2332***
	(0.0237)	(0.0287)	(0.0318)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	955347	711502	710656
Outcome Mean	6.3458	6.7623	6.0292
1 s.d. of $Skill\ ratio_{it}$	0.2461	0.2461	0.2461
Δ Capital Productivity	-	-	0.0027
(% of initial Capital Productivity)	(-)	(-)	(2.47%)

Notes. Estimates are based on the model in Equation (1.3), using firm-year observations over the period 1982-1996. The dependent variable is production (in log) of a firm in a given year in column (1) and (2) while value-added (in log) of a firm in a given year in column (3). ($Skill\ ratio_{it}$) indicates the ratio of skilled-to-unskilled labor in the industry to which a firm belongs. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 1.6: Technology Shift, *forward*

	D.V.= *Log (Production)*		D.V.= *Log (Value-added)*
	(1)	(2)	(3)
	FE	FE	FE
Log (Intermediate)	0.4812***	0.5104***	
	(0.0029)	(0.0038)	
Log (Unskilled)	0.3842***	0.2955***	0.5510***
	(0.0042)	(0.0045)	(0.0069)
Log (Skilled)		0.1027***	0.2258***
		(0.0035)	(0.0055)
Log (Capital)		0.0334***	0.1012***
		(0.0025)	(0.0037)
Log (Intermediate)	0.1239***	0.0409***	
** forward*	(0.0121)	(0.0158)	
Log (Unskilled)	-0.1469***	-0.1348***	-0.0967***
** forward*	(0.0171)	(0.0178)	(0.0276)
Log (Skilled)		0.0637***	0.1408***
** forward*		(0.0140)	(0.0224)
Log (Capital)		0.0387***	0.0550***
** forward*		(0.0101)	(0.0150)
forward	-0.1590**	-0.1267*	-0.0248
	(0.0628)	(0.0735)	(0.0955)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	955347	711502	710656
Outcome Mean	6.3458	6.7623	6.0292
1 s.d. of *Forward*	0.0811	0.0811	0.0811
Δ Capital Productivity	-	0.0031	0.0045
(% of initial Capital Productivity)	(-)	(3.06%)	(4.41%)

Notes. Estimates are based on the model in Equation (1.3), using firm-year observations over the period 1982-1996. The dependent variable is production (in log) of a firm in a given year in column (1) and (2) while value-added (in log) of a firm in a given year in column (3). (*forward*) indicates the weighted sum of the ratio of skilled-to-unskilled labor in the upstream industries with input coefficients as weights. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

1.7 Conclusion

This study sheds light on the key factor of the sustained growth that South Korea has achieved in the post-industrial policy era of the 1980s and 1990s. The expansion of the college enrollment quota in the early 1980s and the subsequent increase in college graduates heading for manufacturing industries served as a big push of adoption good for firms to overcome coordination failure and adopt modern technology under the circumstance of complementarity in technology adoption. As a result, there has been a technological shift from unskilled workers-intensive to skilled workers- and capital-intensive in manufacturing industries since the mid-1980s.

This paper provides empirical evidence for complementarity in technology adoption. The results show that more adopters in the upstream industries increase a marginal adopter's profit and investment and decrease its price. Furthermore, beyond a certain point of skill ratio in the upstream industries turn marginal adopters into positive investment and profit, and negative price in all firm-level regressions in the paper. The break-even upstream skill ratios are 23-32% in investment, 21-36% in profit, and 32-50% in price.

This paper goes on to provide empirical evidence for the technology shift due to human capital accumulation in upstream industries. A weighted sum of skill ratio in the upstream industries increases the value-added elasticity of skilled workers and capital while decreasing that of unskilled workers for firms in all regressions in the paper. Especially, a 1 standard deviation increase in spillover variable increase the capital productivity by 2.47 percent (when $Skill\ ratio_{it}$ is used for spillover variable), and by 3.06 to 4.41 percent (when *forward* is used for spillover variable), respectively, from the initial level of capital productivity with zero spillover.

These results support the theoretical framework I built to explain sustained export-led economic growth in South Korea. Expansion of the college enrollment quota and increased human capital accumulation in upstream industries resulted in a lowered price of intermediate inputs. An individual firm that wants to maximize the benefit of cheaper intermediate goods will adopt modern capital-intensive technology. As a result, demand for capital in the country will increase and the country can delay diminishing returns and sustained export-led economic growth in the post-industrial policy period of the 1980s and the 1990s.

It is important to point out that this paper is based on the assumption that human capital is needed for a firm to adopt modern technology. The specific role of human capital as an adoption good, however, is not discussed. Indeed, there can be many possible roles human capital can play in the process of technology adoption. In the next chapter, I focus on R&D and verify the relationship between R&D spillover and technology shift in South Korea.

Chapter 2

R&D as a Pathway from Human Capital Accumulation to Technology Adoption

2.1 Introduction

This study aims to verify the specific role of human capital in the process of a firm's technology shift toward capital-intensity. In Chapter 1 I build a model incorporating complementarity in technology adoption and a Big Push, and show that an increase in human capital accumulation outside a firm supports that firm's own shift to capital-intensive production techniques. The empirical results demonstrate that it is not profitable for a single firm to accumulate human capital in order to adopt advanced technology if other firms do not do the same. An industry-wide big push of human capital accumulation is needed to overcome coordination failure in technology adoption. The previous paper, however, did not address the specific role that human capital actually plays in the move to modern technology.

To explore this, I first go back to aggregate growth theory. Neoclassical growth models argue that factor accumulation leads to economic growth, but the property of diminishing returns prevents accumulation alone from sustaining growth in per capita terms (Solow, 1956). New growth theory, however, pays attention to Research and Development (R&D) since knowledge, which is the output of R&D, is non-rivalrous and so each firm can use industry-level knowledge in its production process. This non-rivalrous property of knowledge can lead to overcoming diminishing returns and enable countries to sustain economic growth (Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1993).

There is a connection between rivalrous human capital and non-rivalrous knowledge. Indeed, human capital is rivalrous. A firm that hires skilled workers does so in direct competition with other firms. This rivalrous human capital, however, generates non-rivalrous knowledge through innovation activity, or R&D. Many works of literature about the economics of growth refer to this process: if innovation produces spillovers, then education also generates spillovers since education promotes innovation (Nelson and Phelps, 1966); human capital accumulation decides a firm's capacity to yield new ideas or technologies in the production process (Romer, 1990; Benhabib and Spiegel, 1994); there is complementarity between human capital and R&D (Redding, 1996); and empirical evidence supports the idea that human capital accumulation promotes innovative activities like new products and processes (McGuirk et al., 2015). Indeed, firms conduct R&D since they expect that R&D will lead to new products and processes (Arora et al., 2020). But the innovation that makes new products and processes generates technology shifts as well. For example, a conveyor belt requires many workers to do simple tasks, but the innovation of a continuous production process does not require simple workers in complicated production facilities (Goldin and Katz, 1998). The innovation, therefore, promotes a technology shift toward capital-intensive production techniques.

Cohen and Levinthal (1989, 1990) point out that R&D has two faces. It generates new knowledge which is embodied in new products and processes, and it also makes it easier for firms to assimilate outside knowledge produced by other firms' R&D. Many studies examine this spillover effect from outside R&D on a firm's total factor productivity (TFP) growth.[31] Cohen and Levinthal's contribution is to identify a new role for R&D: it increases a firm's capacity to absorb knowledge disseminated from other firms. The authors call this *absorptive capacity*. They use this insight to show how the productivity effect of R&D spillover is increasing in a firm's own R&D investment.

In this paper, I argue that this concept of absorptive capacity[32] perfectly matches the concept of complementarity[33] used in Chapter 1 and analyze the specific role of human capital accumulation with the idea that these concepts are two sides of the same coin. The concept of complementarity – each firm accessing more outside R&D has more incentive to conduct R&D – holds, due to absorptive capacity. Each firm conducting R&D expects to benefit not only directly, through its own innovation but also indirectly, through increased capacity to assimilate outside knowledge. In Chapter 1, I assume that human capital is a necessary input to adopt modern technology.[34] I go on to show that more adopters increase a marginal adopter's gain, and hence, a decision-making firm accessing more human capital accumulation outside the firm is more likely to adopt capital-intensive technology. In this paper, I use R&D as a bridge to connect

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[31] See Griliches (1991) and Mohnen (1996) for surveys of early research.
[32] The effect of R&D spillover is increasing in a firm's own R&D.
[33] The effect of a firm's own R&D is increasing in R&D spillover.
[34] More capital-intensive while less unskilled workers-intensive production techniques.

human capital accumulation and complementarity in technology shift and set up three testable hypotheses. First, the 1980s expansion of the college enrollment quota and subsequent increase in the supply of skilled workers promotes R&D in upstream industries. Second, R&D, which promotes a technology shift toward capital-intensity, increases a firm's absorptive capacity. If the concept of absorptive capacity is proven to be valid, then it also proves the concept of complementarity as well. Third, outside R&D increases a firm's capacity to adopt capital-intensive technology based on the concept of complementarity.

The empirical results support each of these hypotheses. (i) I find that human capital accumulation has a positive effect on R&D: human capital accumulation in the upstream industries increases the positive effect of a firm's skilled-to-unskilled ratio on its R&D spending. (ii) I find that the effect of outside R&D on measures of a firm's performance, such as investment and profit, is increasing in its own R&D in most model specifications. This finding supports the conjecture that R&D serves as a measure of a firm's absorptive capacity. And it also validates the idea of complementarity in technology adoption. (iii) Outside R&D increases the productivity of capital at firm level: a one standard deviation increase in R&D spillover increases capital productivity by 4.71-4.77 percent from the baseline with zero R&D spillover. Contrary to the theoretical prediction, however, the productivity of skilled labor is decreasing and that of unskilled labor is increasing in outside R&D. It leaves room for future studies to fill the gap. Assimilating international R&D spillover, importing technology-embedded capital, or exporting capital-intensive goods would be another candidate pathway from human capital accumulation to technology shift.

My work makes two contributions to the literature on knowledge, human capital and industrial growth. First and foremost, I point out that the concept of complementarity and absorptive capacity are two sides of the same coin. By using this property, I verify that R&D is the channel through which human capital accumulation outside a firm leads to the firm's own technology shift. So, the reason human capital is assumed to be an adoption good in Chapter 1 is that human capital, or skilled labor, is needed to conduct R&D. Through the analytical process in this paper, I reinforce the background ideas of human capital accumulation and the complementarity in technology shift from the previous paper by using the concept of absorptive capacity of R&D. My strategy of synthesizing the concepts of complementarity and absorptive capacity can serve as a reference for future studies.

Second, my work extends aggregate growth theory. Neoclassical growth theory concludes that factor accumulation matters in economic growth but does not fully explain sustained growth due to diminishing returns. New growth theory highlighting the role of R&D and the resulting TFP growth does not explain the East Asian growth miracle which was shown to be heavily dependent on factor accumulation (Nehru and Dhareshwar, 1994; Kim and Lau, 1994; Krugman, 1994; Young, 1995). My analysis shows that outside R&D promotes a firm's technology shift toward capital-intensive production technologies so that it maintains the demand for capital and delays diminishing returns on capital. In other words, my contribution is that my work shows a new way of making sustained growth by putting the views of assimilation and accumulation together. For developing countries, my finding gives a clue to ways in which countries engaged with the global market might alter their comparative advantage from labor-intensive to capital-intensive.

The paper is organized as follows. Section 2.2 shows a literature review. Section 2.3 describes the theoretical framework. Section 2.4 describes the data and Section 2.5 presents the specifications and Section 2.6 shows the conclusion and discussion.

2.2 Literature Review

Neoclassical growth theory considers physical capital accumulation as a key factor for growth and has no role for education in the growth process. The rate of return to physical capital, however, diminishes as capital accumulates, and this leads to decreased incentives for investment. Hence, the theory cannot fully explain sustained growth. Meanwhile, the new growth theory focuses on knowledge accumulation, instead, to explain economic growth. It is called technology if knowledge is embodied in firms, and human capital if knowledge is embodied in people (Grossman and Helpman, 2015). According to Jacobs et al. (2000), the new growth theory can be divided into two parts: (i) human capital-based model, and (ii) research and development (R&D)-based model. The human capital-based model originating with Lucas (1988) considers both physical and human capital together so that it can achieve constant returns to total capital. Furthermore, the model considers that the average level of human capital in the economy can affect an individual firm's performance even though human capital is rivalrous. If this external effect adds up to the constant returns to total capital, the economy can achieve increasing returns to scale (Gemmell, 1998). The R&D-based model, which has its roots in Romer (1990), Aghion and Howitt (1992), and Grossman and Helpman (1993), argues that a firm's R&D activities make technological change and thus lead to economic growth. The result of R&D, knowledge, is non-rivalrous: the original firm's use of knowledge does not preclude its use by other firms. Hence, knowledge can spill over to other firms. This non-rivalrous property offers increasing returns in the production function and a firm can overcome diminishing returns on physical capital (Grossman and Helpman, 2015).

There has been no agreement in the empirical literature on the effect of human capital accumulation on economic growth or total factor productivity (TFP) growth. Mankiw et al.

(1992) add human capital accumulation to the Solow Model (1956) and set up a null hypothesis that there are decreasing returns to total capital, i.e., the sum of physical and human capital. The authors, however, fail to reject the hypothesis of decreasing returns, which means that the Lucas (1988) idea of constant returns to total capital is not supported. Meanwhile, Nelson and Phelps (1966) suggest that it might neglect the relationship between educational attainment and technological progress, or catch up, to include human capital variables directly in the production function. Benhabib and Spiegel (1994) also cast doubt on human capital accumulation as a separate input in the production function since the authors find the effect of human capital on economic growth is insignificant and mostly negative. Rather, they follow the idea of Nelson and Phelps (1966) model and show the growth rate of TFP is increasing in the level of human capital stock. There are other studies, however, reaching the opposite conclusion. Some studies show human capital accumulation plays an important role in the production function to explain economic growth (Nehru and Dhareshwar, 1994; Ballot et al., 2001). Other studies argue that human capital accumulation does not explain TFP growth well (Klenow, 1998; Jacobs et al., 2000).

Although there is no consistent evidence of the relationship between human capital accumulation and TFP growth, there are many studies claiming that human capital accumulation stimulates R&D. Human capital accumulation determines the capacity to innovate new ideas or technologies fitted for production (Romer, 1990; Benhabib and Spiegel, 1994). In the same context, Nelson and Phelps (1966) state that if innovations produce spillovers, then so does education since it promotes innovation. Redding (1996) constructs a model to show complementarity between human capital accumulation and R&D. In the model, the entrepreneur invests more in R&D when workers invest more in human capital, so the expected value of R&D

increases. Likewise, workers invest more in human capital while entrepreneur invests more in R&D so that the expected wage increases. The author states that these interdependent incentives make multiple equilibria[35] possible. McGuirk et al. (2015) provide empirical evidence that human capital accumulation positively affects a firm's innovation activity and the effect is especially large in small firms with less than 50 employees.

Next, I go back to review the R&D-based model. The model is based on the key idea that the result of R&D is non-rivalrous, and hence, it can spill over to other firms and overcome diminishing returns. It is necessary to combine outside R&D into a single spillover variable to measure the spillover effect of R&D. How to set up a weight that is applied to each outside R&D? It should be based on the proximity between outside entity and me. The weights will be smaller if the economic and technological distance from other firms (or industries) increases (Griliches, 1991). Terleckyj (1974) uses an input-output (I-O) table. The idea behind this method is that the more that firms purchase from each other, the more likely it is that there will be spillovers. The input coefficients[36], hence, play a role as weights. The premise of the I-O method is that there is a flow between firm *i* and other firms *j*. Jaffe (1986), however, does not posit flows in a certain direction (Griliches, 1991). Jaffe's (1986) method is based on the idea that the closeness between two firms can be determined by how much they overlap in the distribution of specific patent classes to which patents that they hold belong. If there is a large overlap between two distributions, then both firms have proximity in technological space and there is more benefit from each other's research. Each distribution of patents can be indexed as a technological vector, and the correlation coefficient between two technological vectors will serve as a weight between the two firms.

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[35] (High R&D, High Human Capital), and (Low R&D, Low Human Capital).
[36] The ratio of purchase from other entities divided by total purchase.

There is sufficient evidence showing that R&D spillovers exist, i.e., outside R&D has a positive effect on a firm's TFP (Griliches, 1991; Mohnen, 1996). Both Griliches (1991) and Mohnen (1996) survey inter-industry R&D spillovers and conclude that these exist and are large in magnitude. To be specific, Mohnen (1996) states that R&D's social rate of return is on average 50 to 100 percent greater than its private rate of return. Likewise, Griliches (1991) estimates that the elasticity of output with regard to outside R&D is at most twice as big as the elasticity of output with regard to own R&D. He goes on to show that R&D return accounts for about half of growth in output per worker and three-quarters of TFP growth. Jaffe et al. (1993) try to verify how far knowledge spillover reaches by using patent citations and finds that domestic patents are more likely to be cited domestically. However, there studies of international R&D spillovers finding that R&D conducted by others beyond the border can affect own productivity. Coe and Helpman (1995) use import shares as weights to construct an international spillover variable that is a weighted sum of foreign R&D and conclude that foreign R&D is significantly beneficial to domestic productivity. Keller (2002) uses two different specifications to aggregate spillover variables: one is using the I-O matrix and the other is using the technology flow matrix (T-M) which is based on the information of inventions about where they are produced and they are going to be used. The author generates domestic inter-industry spillover as well as international spillover variables to measure the spillover effect of R&D by using I-O and T-M methods, respectively. The result shows that the I-O method works better than the T-M method, and domestic spillover takes up 30 percent of TFP growth while foreign spillover contributes 20 percent of TFP growth. Many other studies also show that both domestic and foreign R&D spillover effects exist and are beneficial to domestic TFP (Engelbrecht, 1997; Jacobs et al., 2000). In short, these studies provide empirical evidence that other agents' R&D

affect a firm's productivity. However, it is not well addressed in the aforementioned empirical evidence on whether each agent has the capacity required to make use of the R&D spillover effect that other agents produce.

Cohen and Levinthal (1989, 1990) introduce the concept of absorptive capacity. To be specific, R&D generates new knowledge, and also makes it easy for a firm to assimilate existing knowledge outside the firm. The latter role of R&D is called absorptive capacity. The authors argue that how well an agent can make use of spillover from other agents' R&D depends on the agent's own R&D. In other words, the more a firm conducts its own R&D, the more a firm gets R&D spillover from outside firms. This concept of absorptive capacity is equivalent to complementarity in a firm's R&D: The more outside R&D, the more a firm has the incentive to conduct its own R&D to absorb outside R&D. Many studies provide empirical evidence for Cohen and Levinthal's (1989, 1990) absorptive capacity by interacting own R&D and TFP gap (Cameron, 1998; Griffith et al., 2003, 2004; Mannasoo et al., 2018). Teixeira and Fortuna (2010) compare the absorptive capacity of R&D and human capital accumulation. To be specific, the authors consider both human capital accumulation and own R&D as a measure of absorptive capacity and interact the absorptive capacity variables with machinery import, respectively, which is assumed to be outside knowledge. They show that absorptive capacity is bigger when it is measured by R&D than it is represented by human capital accumulation. Aldeiri et al. (2018) consider two types of R&D spillovers and show which countries get more benefit from which R&D spillovers. The authors use two types of R&D spillover:[37] Terleckyj's (1974) I-O method for rent spillover, and Jaffe's (1986) method of proximity in technology space for pure

[37] Griliches (1979) separates knowledge spillover into two parts: One is pure knowledge spillover and the other is rent spillover. Rent spillover occurs when the price of intermediate inputs is not fully reflected for the quality change made by supplier's R&D effort. Pure knowledge spillover occurs when other firm's R&D and the following result of idea is available to own firm.

knowledge spillover. They show that when the countries have the same level of absorptive capacity, countries that are in the frontier of technology get more benefit from pure knowledge spillovers while countries far from the technological frontier get more benefit from rent spillovers.

As stated above, accumulated literature provides empirical evidence to support R&D spillover and its effect on TFP growth. It is based on the non-rivalrous property of knowledge, and this characteristic could enable the country to overcome diminishing returns and achieve sustained growth. The focus of this study, however, is not on verifying the effect of R&D spillover on a firm's TFP growth in South Korea. It is based on many studies in literature showing that East Asian Growth Miracle can be explained by factor accumulation, not by TFP growth (Nehru and Dhareshwar, 1994; Kim and Lau, 1994; Krugman, 1994; Young, 1995). Rather, this study shows the effect of R&D spillover on a firm's technology shift toward capital-intensive production techniques.

2.3 Theoretical Framework

This paper explores whether the specific role of human capital in the process of technology shift is to conduct R&D. Cohen and Levinthal (1989, 1990) suggest a concept of absorptive capacity and many works in the literature provide empirical evidence to support that the fraction of R&D spillover a firm can assimilate increases as the firm conducts more of its own R&D. The evidence can support complementarity in technology adoption as well. When there are more other firms conducting R&D to adopt modern technology, it is beneficial for a firm to conduct more own R&D to increase the fraction the firm can absorb from the R&D spillover. Indeed, both properties of R&D, absorptive capacity and complementarity, are the two sides of the same coin. In this context, R&D spillover would promote a firm's technology shift toward capital-intensity like outside human capital accumulation facilitates a firm's technology shift in Chapter1.

Cohen and Levinthal (1989, 1990) suggest a model of absorptive capacity as follows.

$$z_i = M_i + \gamma_i(\theta \sum_{j \neq i} M_j + T)$$

where z_i is firm i's stock of knowledge and M_i is firm i's own R&D, while $\sum_{j \neq i} M_j$ is the sum of other firms' R&D, θ is the degree of spillover from other firms' R&D and γ_i is a fraction of outside knowledge that firm i can absorb, i.e., its absorptive capacity; and T is a measure of extra-industry knowledge. The model assumes that $\frac{d\gamma_i}{dM_i} > 0$, which means a firm's own R&D increases its absorptive capacity. The model authors suggest above is notable for (i) differentiating a degree of spillover from outside R&D (θ) and a firm's capacity to assimilate it (γ_i), and (ii) suggesting that own R&D increases its absorptive capacity ($\frac{d\gamma_i}{dM_i} > 0$). However, their model does not provide a mechanism behind the absorptive capacity itself.

To address this, in this paper I use the theoretical framework of complementarity due to Buera et al. (2021) and described in Chapter 1 to set up a model of absorptive capacity. My approach exploits the symmetry of these two phenomena in terms of their effects at firm level. Suppose there exists a mass one of firms producing a differentiated good $j \in [0,1]$ respectively using unskilled labor (*l*) and intermediate goods (*x*).

$$y = \frac{A_i}{v_i^{v_i}(1-v_i)^{1-v_i}} l^{1-v_i} x^{v_i} \quad where\ v_i{}^{38} \in [0,1]\ and\ i \in \{t, m\}$$

Modern technology (*m*) is assumed to be more productive,

$$\frac{A_m}{v_m^{v_m}(1-v_m)^{1-v_m}} > \frac{A_t}{v_t^{v_t}(1-v_t)^{1-v_t}}$$

And is more intermediate goods-intensive than the traditional technology (*t*) which is unskilled labor-intensive.

$$v_m > v_t$$

Adopting modern technology requires an adoption cost of conducting R&D. These adoption goods enable the adopting firm to depend less on unskilled workers and to improve the productivity of intermediate goods it produces.

The differentiated goods are combined into an intermediate aggregate,

$$X = \left[\int y_j^{\frac{\eta-1}{\eta}} dj\right]^{\frac{\eta}{\eta-1}}$$

Where η, the elasticity of substitution, is assumed to be greater than 1.

Then the demand for the differentiated good *j* is

$$y_j = \left(\frac{P}{p_j}\right)^{\eta} X$$

[38] v_i is the intermediate input elasticity.

where P, the price index of the intermediate aggregate is

$$P = \left[\int p_j^{1-\eta} dj \right]^{\frac{1}{1-\eta}}$$

In the model above, more adopting firms decrease the price (P) of the intermediate aggregate since modern technology is more productive. It forces a decision-making firm to decrease its price to compete with the aggregate, and thus the firm's profit decreases. This is called the competition effect. However, a decrease in the price of intermediate aggregate also leads to a decrease in the cost of intermediate inputs purchased by the firm, and an increase in the demand for its output. If the latter effects are bigger than the competition effect such that the marginal adopting firm's profit is increasing in the number of adopters outside the firm, then complementarity in technology adoption holds. In this case, a fraction of the benefit (γ_i) that the firm absorbs from outside R&D would be increased if the firm chooses to conduct R&D and adopt modern technology which is more intermediate input-intensive.[39]

Based on the literature and the theoretical framework above, I set up three testable hypotheses as follows: First, human capital accumulation has a positive effect on R&D. Human capital accumulation, which is assumed to be an adoption good in Chapter 1, is hypothesized to promote R&D, increasing the likelihood that a firm can profitably adopt modern technology. Second, a firm's own R&D increases its absorptive capacity for assimilating R&D spillover. This hypothesis is equivalent to the statement that the effect of other firms' R&D is increasing in a firm's own R&D. It can be verified in the regression of profit on own R&D, R&D spillover, and the interaction of both. If the answer is yes, in other words, the coefficient on the interaction

[39] Modern technology is also more capital-intensive. Modern technology depends less on unskilled labor but more on intermediate inputs. Introducing advanced capital that substitutes for unskilled labor and produces more output with the same amounts of intermediate inputs would be an exemplary of modern technology.

variable is positive, then the result induces complementarity as well, i.e., the effect of own R&D is increasing in other agents' R&D. Third, outside R&D promotes a firm's technology shift. Due to the change in the education policy, human capital accumulation in manufacturing industries increases. According to the first testable hypothesis, human capital accumulation has a positive effect on R&D. If it is supported by evidence, then R&D in upstream industries increases as well, due to the policy change. Failure to reject the second hypothesis would verify R&D's absorptive capacity and demonstrate that complementarity holds: more outside R&D increases the gain of a marginal firm doing R&D. So, a firm facing increased outside R&D would conduct R&D to adopt modern technology which is more capital-intensive and less unskilled labor-intensive.

2.4 Data

The previous paper assumes human capital as an adoption good for technology adoption and examines whether the expansion of the college enrollment quota and the subsequent human capital accumulation in the upstream industries promote a firm's technology shift. This paper aims to investigate the specific role of human capital in the technology process which is just assumed to be adoption good for advanced production technique in Chapter 1. Based on the literature review of aggregate growth theory and absorptive capacity of R&D, I point out that one of the roles that human capital does in the process of technology shift is to conduct R&D. Hence, I use the same dataset used in Chapter 1, and merge R&D data into the existing dataset to examine hypotheses in the specification session.

I again use panel data between 1982-1996 from Mining and Manufacturing Survey[40] (MMS). It is plant-level data from a yearly census by Statistics Korea. The dataset contains variables such as production, value-added, capital, investment, sales and profit, and the number of employees for both blue-collar (unskilled) and white-collar (skilled) workers in each plant. In some years, the MMS panel dataset is augmented with R&D data. A questionnaire about each firm's R&D activities was included in the MMS survey in 1983, 1988, and 1993 through 2000. So, R&D data is also plant-level panel data from a census. I obtained the R&D data through an additional request[41] to Statistics Korea. As the MMS dataset used in Chapter 1 covers years between 1982 and 1996, I could choose R&D data in 1983, 1988, 1993, 1994, 1995, and 1996. However, I actually include the R&D data from 1983, 1988, 1993, and 1996 only, so that there are almost even gaps between years: two 5-year gaps and one 3-year gap. The R&D data

[40] MMS data can be accessed only remotely and cannot be carried out. Graphs and tables generated from the data have to be reviewed by the Statistics Korea before they can be downloaded. The review takes 5 to 7 business days.
[41] R&D data is not included in the published MMS data by Statistics Korea.

includes R&D expenditures such as labor, material, equipment and structures, and the total amount of R&D expenditure. It also includes the firm's identification number, so I can merge R&D data into the existing MMS panel dataset.

I also use the Input-Output (IO) table in 1980 to get a spillover variable. Using the IO table is valid in the specification since the theoretical framework uses intermediate inputs in the production function to consider inter-industry spillover and the IO table is a cross table of how much intermediate inputs are supplied between industries. I use the input coefficients[42] as weights to construct a spillover variable that is a weighted sum of the R&D ratio in the upstream industries. I mainly use R&D-to-sales ratio in the analysis, and for robustness checks I also use R&D-to-profit and R&D-to-production ratios. I still assume trade patterns among domestic industries in 1980 are maintained over 1982-1996.

Data cleaning processes are conducted in the same way as done in the previous paper. Development outcomes such as production, value-added, sales, profit, and R&D are discounted by the industry-level Producer Price Index (PPI) to get 2015-year values, and capital and investment are discounted to become real value by using a capital deflator for each type of formation[43]. Groups of MMS data based on different industrial codes[44] are harmonized to the recent code of the 6th Korean Standard Industry Code (KSIC), and the harmonized MMS panel and IO table are harmonized again since they use different classifications of industry.

[42] A portion of intermediate input bought from each supplier industry.
[43] There are three types of capital formation: building and structure, machinery and equipment, and vehicles.
[44] MMS in 1982 is based on KSIC 4th, MMS in 1983-1989 are based on KSIC 5th, and MMS in 1990-1996 are based on KSIC 6th.

Table 2.1: Descriptive Statistics

	All 4-year	1983	1988	1993	1996
# Firms	284,904	39,129	59,800	88,870	97,105
Skilled labor	9.2660	10.4519	11.0450	8.5614	8.3376
	(86.3188)	(71.4057)	(80.9635)	(77.7689)	(101.1473)
Unskilled labor	29.3076	46.0270	40.5143	23.2315	21.2298
	(188.8867)	(258.9279)	(227.867)	(145.6833)	(161.1709)
Capital	1832.426	1215.868	1498.515	1883.365	2239.884
	(33643.42)	(28439.87)	(26109.62)	(35036.11)	(38097.04)
R&D spending	41.1358	21.3598	22.4223	43.3396	58.6121
	(1448.1)	(598.6)	(521.554)	(1255.5)	(2096.9)
Skill ratio[45]	0.3135	0.2372	0.2805	0.3412	0.3386
	(0.7960)	(0.4291)	(0.4974)	(0.7215)	(1.0710)
Forward[46]	0.2301	0.1840	0.2080	0.2383	0.2547
	(0.0825)	(0.0802)	(0.0779)	(0.0755)	(0.0814)
R&D-sales ratio	0.0079	0.0043	0.0075	0.0101	0.0077
	(0.4058)	(0.0388)	(0.6161)	(0.5031)	(0.1247)
R&D-sales spillover[47]	0.0042	0.0030	0.0029	0.0056	0.0042
	(0.0037)	(0.0024)	(0.0020)	(0.0052)	(0.0026)
R&D-production ratio	0.0058	0.0040	0.0046	0.0072	0.0061
	(0.2959)	(0.1208)	(0.2860)	(0.4222)	(0.1938)
R&D-production spillover	0.0040	0.0028	0.0028	0.0053	0.0040
	(0.0036)	(0.0023)	(0.0020)	(0.0052)	(0.0025)
Investment	374.6224	180.6859	357.931	338.5866	496.0289
	(9671.988)	(4007.955)	(6895.069)	(6868.678)	(13982.45)
Profit	1788.047	1006.96	1364.729	1848.008	2308.604
	(32791.03)	(15116.99)	(22200.86)	(34093.2)	(41167.62)
Price	88.1698	77.27393	94.9960	87.7200	88.7682
	(230.2083)	(306.4587)	(342.3792)	(172.9268)	(134.2094)
Industry-level controls					
Production-Capital ratio	3.6658	3.6186	3.8467	3.4597	3.7619
	(2.2548)	(2.5100)	(2.4636)	(2.0291)	(2.1916)
Production-Labor ratio	109.3648	44.6815	65.4602	112.8968	159.2339
	(141.4899)	(88.5254)	(97.1904)	(133.8308)	(167.3283)
Value added-Production ratio	0.4489	0.4162	0.4105	0.4692	0.4672
	(0.0910)	(0.0983)	(0.0877)	(0.0874)	(0.0815)
Profit-Production ratio	0.3403	0.3245	0.3257	0.3510	0.3458
	(0.1656)	(0.1421)	(0.1262)	(0.1775)	(0.1824)
Profit-Sales ratio	0.2663	0.3198	0.3402	0.2880	0.1795
	(0.8307)	(0.3445)	(0.1656)	(0.6290)	(1.2590)

45 $Skill\ ratio = \left(\frac{Skilled}{Unskilled}\right)_{ijt}$

46 $Forward = \sum_k \alpha_{ki} \left(\frac{Skilled}{Unskilled}\right)_{kt}$

47 $R\&D\ spillover = \sum_k \alpha_{ki} \left(\frac{R\&D}{Sales}\right)_{kt}$

2.5 Specification

Many works in literature argue that human capital accumulation raises a firm's innovative R&D activities (Nelson and Phelps, 1966; Romer, 1990; Benhabib and Spiegel, 1994; Redding, 1996; McGuirk et al., 2015). Based on these works, it is predictable that firm's R&D activities would increase after the expansion of the college enrollment quota in the early 1980s in South Korea. I first verify whether the human capital accumulation increases total R&D spending in firms in manufacturing industries. And then, I examine whether R&D's property of absorptive capacity holds. Cohen and Levinthal (1989, 1990) argues that the effect of R&D spillover is increasing in a firm's own R&D. Many studies provide empirical evidence of absorptive capacity by interacting own R&D and spillover of R&D (Cameron, 1998; Griffith et al., 2003, 2004; Teixeira and Fontana, 2010; Mannasoo et al., 2018). If this property of absorptive capacity holds, and if R&D is assumed to be an activity to adopt advanced production technique, then complementarity in technology adoption (the effect of own R&D is increasing in R&D spillover) is also verified in the same specification. Finally, I use the property of complementarity to verify whether outside R&D promotes a firm's technology shift toward capital-intensive production technique.

2.5.1 Human capital accumulation and R&D

To examine the relationship between human capital accumulation and R&D, I estimate a series of fixed effect regression models of the form

$$(2.1)\quad Outcome_{ijt} = \beta_0 + \beta_S(Skill\ ratio)_{ijt} + \beta_F(Forward)_{it}$$

$$+\beta_{SF}(Skill\ ratio)_{ijt}(Forward)_{it} + \mathrm{W}_{it}^{'}\Gamma + \alpha_j + \delta_t + \varepsilon_{ijt}$$

where $Outcome_{ijt}$ is a firm's total R&D spending, and $Skill\ ratio_{ijt}$ is the ratio of skilled-to-unskilled labor (hereafter *skillratio*) in firm j in industry *i* in time *t*.[48] $Forward_{it}$ is the weighted sum of skilled-to-unskilled ratios (hereafter *forward*) in *i*'s upstream industries *k* in time *t* with input coefficients in the 1980 I-O table as weights. The vector W_{it} indicates a set of industry characteristics of average productivity ($\frac{Production}{Captial}$, $\frac{Production}{Labor}$, $\frac{Value-added}{Production}$), profitability ($\frac{Profit}{Production}$, $\frac{Profit}{Sales}$), and trade[49] ($\sum_{t=1982}^{1996}\left(\frac{exports}{total\ supply}\right)_{i1980} * Year_t$, $\sum_{t=1982}^{1996}\left(\frac{imports}{total\ supply}\right)_{i1980} * Year_t$). I also adopt firm- ($\alpha_j$) and time-fixed effects (δ_t) to eliminate firm-specific characteristics over time and year-specific properties across firms. An error term ε_{ijt} refers to unobserved characteristics that affect a firm's $Outcome_{ijt}$. Standard errors are clustered at a firm level and robust to heteroskedasticity.

Industry-level variables, *forward* and W_{it}, come from outside a firm. But a firm's *skillratio* is a firm-level variable and it could be endogenous. To be specific, a firm's unobserved features in the error term, ε_{ijt}, could affect both *skillratio* and $Outcome_{ijt}$, and also there could be a reverse causality between them. I adopt one- and two-time lagged *skillratios* as instrumental variables to resolve endogeneity in *skillratio*. It is legitimate to argue that instruments are exogenous provided that time gap is five-year (three-year in the last gap) and it is less likely that shocks are effective for more than ten years and affect both instruments and the current outcome variables. Also, I argue instruments are relevant since endogenous regressor and instruments capture the same characteristics, skilled-to-unskilled labor ratios, but are based on different time.

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[48] Dataset includes data in 1983, 1988, 1993, and 1996. Time 1, 2, 3, and 4 refer to year 1983, 1988, 1993, and 1996, respectively.

[49] Exports, imports, and total supply (=total output + imports) come from 1980 I/O table. The ratio of exports-to-total supply and imports-to-total supply are interacted with year dummies.

First stage regressions are given by

$$(2.2) \quad (Skill\, ratio)_{ijt} = b_0 + Z_{ijt-2}^{t-1} b_s + Z_{ijt-2}^{t-1} (Forward)_{it} b_{sf}$$

$$+ b_f (Forward)_{it} + \mathrm{W}_{it}^{'} \mathrm{c} + a_j + d_t + e_{ijt}$$

$$(Skill\, ratio)_{ijt} (Forward)_{it} = b_{1,0} + Z_{ijt-2}^{t-1} b_{1,s} + Z_{ijt-2}^{t-1} (Forward)_{it} b_{1,sf}$$

$$+ b_{1,f} (Forward)_{it} + \mathrm{W}_{it}^{'} \mathrm{c}_1 + a_{1,j} + d_{1,t} + e_{1,ijt}$$

where Z_{ijt-2}^{t-1} is a vector of one- and two-time lagged *skillratios*. The remainder of the notation is the same as in Equation (2.1).

Table 2.2 presents results from estimating variants of Equation (2.1). All columns indicate a negative relationship between a firm's *skillratio* and total R&D spending when *forward* is zero. However, the negative relationship shrinks in magnitude and turns positive as *forward* increases since coefficients on interaction variable, *skillratio* * *forward*, are positive in all columns. The break-even ratios of *forward* are 24-37 percent. The results show that human capital accumulation in the upstream supplier industries promotes a positive relationship between a firm's skilled-to-unskilled labor ratio and total R&D spending.

Table 2.2: Complementarity: Total R&D spending and skilled-to-unskilled ratio

Total R&D spending	(1) FE	(2) FE+IV	(3) FE	(4) FE+IV	(5) FE	(6) FE+IV	(7) FE	(8) FE+IV
skillratio	-22.3884*	-261.1194	-34.4282*	-215.1198	-23.7533*	-213.9186	-23.5143*	-220.6181
	(12.9829)	(273.6830)	(13.1399)	(259.4834)	(13.1817)	(259.8526)	(13.1103)	(249.4058)
forward	389.9868*	-70.5824	694.9957***	291.7305	698.7332***	119.9474	740.4597***	94.0389
	(236.6552)	(1356.0855)	(252.0148)	(1368.7588)	(252.3548)	(1381.5226)	(279.9175)	(1459.5663)
skillratio * *forward*	91.6701**	728.0339	95.2132**	592.7634	96.2111**	584.6888	95.0859**	601.1888
	(43.0659)	(745.7066)	(42.9160)	(709.0691)	(43.1541)	(705.6927)	(43.1552)	(679.7266)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry-level Controls								
Productivity	N	N	Y	Y	Y	Y	Y	Y
Profitability	N	N	N	N	Y	Y	Y	Y
Trade	N	N	N	N	N	N	Y	Y
Observations	278765	17610	278765	17610	278751	17606	276251	17174
Outcome Mean	41.7812	208.0128	41.7812	208.0128	41.7833	208.0398	41.1358	41.1358
K-P p-value	-	0.3943	-	0.3918	-	0.3908	-	0.3982
Hansen J p-value	-	0.2398	-	0.2618	-	0.2679	-	0.2626
Break-even Forward ratio	0.2442	0.3587	0.3616	0.3629	0.2469	0.3659	0.2473	0.3670

Notes. Estimates are based on the model in Equation (2.1), using firm-year observations over the year 1983, 1988, 1993, and 1996. The dependent variable is total R&D spending of a firm in a given year. *skillratio* indicates the ratio of skilled-to-unskilled labor and *forward* indicates the weighted sum of the ratio of skilled-to-unskilled labor in the upstream industries with input coefficients as weights. I apply two-stage least square (IV) method in column (2), (4), (6), and (8) using Equation (2.2) as first-stage regression. Controls for productivity include industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include industry-level ratios of profit-to-production, and profit-to-sales. Controls for trade include exports-to-total supply ratios and imports-to-total supply ratios in 1980 I-O table interacted with year dummies. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

2.5.2 The absorptive capacity of R&D

I go on to examine whether R&D has a face of absorptive capacity: the effect of R&D spillover is increasing in the own R&D. To examine the relationship between own R&D, outside R&D (spillover), and a firm's outcome (price, profit, and investment), I estimate a series of fixed effect model

(2.3) $Outcome_{ijt} = \beta_0 + \beta_R (R\&D\ ratio)_{ijt} + \beta_S (R\&D\ Spillover)_{it}$

$$+\beta_{RS}(R\&D\ ratio)_{ijt}(R\&D\ Spillover)_{it} + \mathrm{W}_{it}^{'}\Gamma + \alpha_j + \delta_t + \varepsilon_{ijt}$$

where $Outcome_{ijt}$ is either a firm's investment, profit, or price, and $R\&D\ ratio_{ijt}$ is the ratio of R&D-to-sales or R&D-to-production (hereafter *rndratio*) in firm *j* in industry *i* in time *t*. $R\&D\ spillover_{it}$ is the weighted sum of R&D ratios (hereafter *spillover*) in *i*'s upstream industries *k* in time *t* with input coefficients in 1980 I-O table as weights.[50] The vector W_{it} indicates a set of industry characteristics of average productivity ($\frac{Production}{Captial}, \frac{Production}{Labor^{51}}, \frac{Value-added}{Production}$), profitability ($\frac{Profit}{Production}, \frac{Profit}{Sales}$), and trade ($\sum_{t=1982}^{1996} \left(\frac{exports}{total\ supply}\right)_{i1980} Year_t,\ \sum_{t=1982}^{1996} \left(\frac{imports}{total\ supply}\right)_{i1980} Year_t$). I also adopt firm- ($\alpha_j$) and time-fixed effects (δ_t) to get rid of firm-specific characteristics over time and properties year-specific across firms. An error term ε_{ijt} represents unobserved characteristics that affect a firm's $Outcome_{ijt}$. Standard errors are clustered at a firm level and robust to heteroskedasticity. While $spillover$ is exogenous, a firm's $rndratio$ could bring endogeneity issues: a firm's unobserved characteristics could affect both $rndratio$ and $Outcome_{ijt}$, and there could exist reverse causality as well. To address endogeneity in $rndratio$, I adopt as instrumental variables

[50] $R\&D\ spillover_{it} = \sum_k \alpha_{ki} (R\&D\ ratio)_{kt}$
[51] Labor is a sum of skilled and unskilled labor.

$skillratio, forward$, and the interaction $skillratio * forward$. The merit of this approach is to verify the effect of human capital accumulation on a firm's performance through the channel of R&D activity. First stage regressions are given by

(2.4) $$(R\&D\ ratio)_{ijt} = b_0 + Z_{ijt}b_r + Z_{ijt}(R\&D\ spillover)_{it}b_{rs}$$

$$+b_s(R\&D\ spillover)_{it} + \mathrm{W}_{it}^{'}\mathrm{c} + a_j + d_t + e_{ijt}$$

$$(R\&D\ ratio)_{ijt}(R\&D\ spillover)_{it} = b_{1,0} + Z_{ijt}b_{1,r} + Z_{ijt}(R\&D\ spillover)_{it}b_{1,rs}$$

$$+b_s(R\&D\ spillover)_{it} + \mathrm{W}_{it}^{'}\mathrm{c}_1 + a_{1,j} + d_{1,t} + e_{1,ijt}$$

where Z_{ijt} is a vector of $skillratio, forward$, and $skillratio * forward$. The remainder of the notation is the same as in Equation (2.3).

The parameter of interest in the Equation (2.3) is β_{RS}, which is the coefficient on the interaction variable of own *rndratio* and *spillover*. It verifies absorptive capacity (the effect of R&D spillover is increasing in its own R&D) and complementarity (the effect of own R&D is increasing in R&D spillover) simultaneously.

The theoretical framework predicts a decrease in the price of the intermediate aggregate when there is an increase in R&D in the upstream industries. It reduces a firm's price of its product and it leads to a shrink in the firm's profit (it is called competition effect). However, a decrease in the price of intermediate aggregate also increases the demand for the firm's product and also decreases the cost of material the firm uses to produce its product. These two effects inflate the firm's profit. If the latter two effects outweigh the competition effect, then the firm conducts R&D and adopts intermediate input-intensive modern technology to get more from cheaper intermediate inputs. As a result, there exists complementarity in technology adoption: more outside adopters increase the marginal adopter's gain.

Table 2.3, 2.4, and 2.5 present the results from estimating variants of Equation (2.2) when $Outcome_{ijt}$ is profit, investment, and price, respectively. In these tables, first two columns (1) and (2) use R&D-to-sales ratio, next two columns (3) and (4) use R&D-to-production ratio to measure a firm's $rndratio$. Table 2.3 is the results of estimating variants of Equation (2.3) when profit is used in $Outcome_{ijt}$. Each column shows that a coefficient on the interaction variable is positive (except column (3)). The results verify that R&D has a face of absorptive capacity: the effect of R&D spillover is increasing in own R&D. Also, there is complementarity in R&D activity: The effect of own R&D is increasing in R&D spillover (more adopters increase marginal adopter's gain). The break-even ratios of outside R&D (*spillover*) are 0.0036-0.0047 when R&D ratio is measured by R&D-sales ratio, and 0.0061 when R&D ratio indicates R&D-production ratio. Beyond the break-even $spillover$, a unit increase of a firm's own R&D is positively associated with its profit.

Table 2.3: Complementarity: Profit

D.V.=Profit	R&D-to-sales		R&D-to-production	
	(1)	(2)	(3)	(4)
	FE	FE+IV	FE	FE+IV
rndratio	-185	-505381*	105	-392238
	(217)	(289349)	(420)	(253727)
spillover	15065	-406710*	29916	-230567**
	(25110)	(222716)	(20126)	(116067)
rndratio	51042	107550000*	-34146	63932564**
* *spillover*	(64921)	(56073371)	(132509)	(30304516)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry-level Controls				
Productivity	Y	Y	Y	Y
Profitability	Y	Y	Y	Y
Trade	Y	Y	Y	Y
Observations	221696	126365	282215	163930
Outcome Mean	2325	2366	1789	1814
K-P p-value	-	0.1058	-	0.0681
Hansen J p-value	-	0.4607	-	0.4585
Break-even Forward ratio	0.0036	0.0047	-	0.0061

Notes. Estimates are based on the model in Equation (2.3), using firm-year observations over the year 1983, 1988, 1993, and 1996. The dependent variable is profit of a firm in a given year. *rndratio* indicates the ratio of R&D-to-sales in column (1) and (2), and the ratio of R&D-to-production in column (3) and (4). *spillover* indicates the weighted sum of the ratio of R&D-to-sales in the upstream industries with input coefficients as weights in column (1) and (2) while R&D spillover indicates the weighted sum of the ratio of R&D-to-production in the upstream industries with input coefficients as weights in column (3) and (4). I apply two-stage least square (IV) method in column (2) and (4) using Equation (2.4) as first-stage regression. Controls for productivity include industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include industry-level ratios of profit-to-production, and profit-to-sales. Controls for trade include exports-to-total supply ratios and imports-to-total supply ratios in 1980 I-O table interacted with year dummies. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 2.4 shows estimates of Equation (2.3) when dependent variable is a firm's investment. All columns show that the coefficient on the interaction variable is positive. The results also verify that R&D has a face of absorptive capacity and a property of complementarity in R&D. The break-even ratios of outside R&D are 0.0031-0.0040 when R&D ratio is measured by R&D-sales ratio, and 0.0031-0.0047 when R&D ratio indicates R&D-production ratio. Beyond the break-even $spillover$, a unit increase of a firm's own R&D is positively associated with its investment.

Table 2.4: Complementarity: Investment

D.V.=Investment	R&D-to-Sales		R&D-to-Production	
	(1)	(2)	(3)	(4)
	FE	FE+IV	FE	FE+IV
rndratio	-376	-26552	-617***	-22161
	(359)	(36278)	(151)	(29239)
spillover	-2457	-27210	-4215	-21932
	(4759)	(33421)	(4145)	(19286)
rndratio * *spillover*	122705	6647208	201071***	4736009
	(112718)	(8573897)	(44317)	(4613359)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry-level Controls				
Productivity	Y	Y	Y	Y
Profitability	Y	Y	Y	Y
Trade	Y	Y	Y	Y
Observations	221696	126365	282215	163930
Outcome Mean	452	463	370	378
K-P p-value	-	0.1058	-	0.0681
Hansen J p-value	-	0.5349	-	0.6562
Break-even Forward ratio	0.0031	0.0040	0.0031	0.0047

Notes. Estimates are based on the model in Equation (2.3), using firm-year observations over the year 1983, 1988, 1993, and 1996. The dependent variable is investment of a firm in a given year. *rndratio* indicates the ratio of R&D-to-sales in column (1) and (2), and the ratio of R&D-to-production in column (3) and (4). *spillover* indicates the weighted sum of the ratio of R&D-to-sales in the upstream industries with input coefficients as weights in column (1) and (2) while R&D spillover indicates the weighted sum of the ratio of R&D-to-production in the upstream industries with input coefficients as weights in column (3) and (4). I apply two-stage least square (IV) method in column (2) and (4) using Equation (2.4) as first-stage regression. Controls for productivity include industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include industry-level ratios of profit-to-production, and profit-to-sales. Controls for trade include exports-to-total supply ratios and imports-to-total supply ratios in 1980 I-O table interacted with year dummies. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 2.5 shows estimates of Equation (2.3) when $Outcome_{ijt}$ is price. Each column shows that a coefficient on the interaction variable is negative (except column (3)). The results also verify that R&D has a face of absorptive capacity and a property of complementarity in R&D. The break-even ratios of outside R&D are 0.0061-0.0119 when R&D ratio is measured by R&D-sales ratio, and 0.0088 when R&D ratio indicates R&D-production ratio. Beyond the break-even ratio of outside R&D, marginal adopters who increase a unit of its own R&D will lead to a lowered price.

Table 2.5: Complementarity: Price

D.V.=Price	R&D-to-Sales		R&D-to-Production	
	(1)	(2)	(3)	(4)
	FE	FE+IV	FE	FE+IV
rndratio	4^{**}	2712^{*}	2	3023
	(2)	(1466)	(2)	(1872)
spillover	-441^{***}	1355	-303^{***}	1178^{**}
	(43)	(842)	(33)	(599)
rndratio	-337	-443909^{**}	373	-344508^{**}
* *spillover*	(413)	(206973)	(603)	(152285)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry-level Controls				
Productivity	Y	Y	Y	Y
Profitability	Y	Y	Y	Y
Trade	Y	Y	Y	Y
Observations	221696	126365	282215	163930
Outcome Mean	86	86	88	89
K-P p-value	-	0.1058	-	0.0681
Hansen J p-value	-	0.9585	-	0.5753
Break-even Forward ratio	0.0119	0.0061	-	0.0088

Notes. Estimates are based on the model in Equation (2.3), using firm-year observations over the year 1983, 1988, 1993, and 1996. The dependent variable is price of a firm in a given year. *rndratio* indicates the ratio of R&D-to-sales in column (1) and (2), and the ratio of R&D-to-production in column (3) and (4). *spillover* indicates the weighted sum of the ratio of R&D-to-sales in the upstream industries with input coefficients as weights in column (1) and (2) while R&D spillover indicates the weighted sum of the ratio of R&D-to-production in the upstream industries with input coefficients as weights in column (3) and (4). I apply two-stage least square (IV) method in column (2) and (4) using Equation (2.4) as first-stage regression. Controls for productivity include industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include industry-level ratios of profit-to-production, and profit-to-sales. Controls for trade include exports-to-total supply ratios and imports-to-total supply ratios in 1980 I-O table interacted with year dummies. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

2.5.3 Technology Shift

To examine the direction of technology shift for a firm accessing an increased R&D spillover, I build a model by taking a log on Cobb-Douglas production function and interacting logged inputs with a R&D spillover variable. I estimate the model

(2.5) $Y_{ijt} = X'_{ijt}\beta + (R\&D\ Spillover)_{it}X'_{ijt}\gamma + \alpha_j + \delta_t + \varepsilon_{ijt}$

where Y_{ijt} is a log of value-added[52] and X_{ijt} is a vector of logged inputs (skilled labor, unskilled labor, and capital) in firm *j* in industry *i* in time *t*. A variable of $R\&D\ spillover_{it}$ (*spillover*) is a weighted sum of R&D ratio in the upstream industries with input coefficients as weights. To check robustness, I use different source of *rndratio* (R&D-to-sales or R&D-to-production) to construct *spillover* and see whether the results from different measures have similar patterns. The variables α_j and δ_t represent firm- and year-fixed effect respectively to get rid of firm-specific characteristics over time and year-specific properties across entities. The error term ε_{ijt} refers to unobservable characteristics. Standard errors are clustered at a firm level. In Equation (2.5), there is a concern that unobserved productivity shock in the error term could be correlated with both (logged) inputs and value-added. I use the Levinsohn-Petrin[53] (L-P) method to address this endogeneity problem in the identification of the Cobb-Douglas production function. Details for applying L-P methods are shown in Appendix B.2.

[52] Plant-level value-added data is available in MMS dataset. It is the value of production minus intermediate inputs used for production.

[53] Levinsohn-Petrin (2003) use intermediate inputs as proxies for unobserved productivity shock. Their method resolves the problem of zero investment in a nontrivial number of firms in Olley-Pakes (1996), which uses investment as a proxy.

Table 2.6 presents the results from estimating variants of Equation (2.5). Column (1) uses R&D-to-sales ratio to construct *spillover* variables, while Column (2) uses R&D-to-production ratio. Both columns show positive coefficients on capital interacted with *spillover*, which means outside R&D increases a firm's marginal productivity of capital. Both columns show positive coefficients on unskilled labor interacted with *spillover*, while there are negative coefficients on the interaction variable of skilled labor interacted with *spillover*. These results indicate that outside R&D promotes a firm's technology shift toward capital- and unskilled labor-intensive production technique. Especially, a 1 standard deviation increase in *spillover* increases the capital productivity by 4.71 percent (R&D-sales ratio), and 4.77 percent (R&D-production ratio), respectively, from the initial level of capital productivity with zero *spillover*.

It is remarkable to note that domestic *spillover* increases productivity of capital. This direction of technology shift helps delay diminishing returns on capital. Also, the direction of technology shift induced by domestic *spillover* is more unskilled-labor intensive but less skilled-labor intensive. It may be understood in the context that the country was at the initial level of R&D activity in the 1980s and 1990s, and hence, domestic *spillover* could have a limited effect. The direction of technology shift would be different if international R&D or imported capital are considered in the spillover variable. It would be also meaningful to consider the role of human capital accumulation in the process of international R&D spillover and/or trade such as importing advanced technology-embedded machinery and promoting to export capital-intensive goods abroad.

Table 2.6: Technology Shift

D.V.=Log (Value-added)	R&D-to-sales	R&D-to-production
	(1)	(2)
	FE	FE
Log (Unskilled)	0.5366***	0.5372***
	(0.0065)	(0.0065)
Log (Skilled)	0.2932***	0.2934***
	(0.0054)	(0.0054)
Log (Capital)	0.1138***	0.1138***
	(0.0037)	(0.0037)
*Log (Unskilled) * spillover*	1.3926*	1.3033
	(0.8399)	(0.8607)
*Log (Skilled) * spillover*	-1.4661**	-1.6018**
	(0.7408)	(0.7503)
*Log (Capital) * spillover*	1.4483***	1.5085***
	(0.4962)	(0.5038)
spillover	-9.4215***	-9.5408***
	(2.2373)	(2.2654)
Firm FE	Y	Y
Year FE	Y	Y
Observations	202050	202050
Outcome Mean	6.1454	6.1454
Δ 1 s.d. of *R&D Spillover*	0.0037	0.0036
Δ Capital Productivity	0.0054	0.0054
(% of initial Capital Productivity)	(4.71%)	(4.77%)

Notes. Estimates are based on the model in Equation (5), using firm-year observations over the period 1983, 1988, 1993, and 1996. The dependent variable is value-added (in log) of a firm in a given year. (*spillover*) refers to the weighted sum of the ratio of R&D-to-sales in the upstream industries with input coefficients as weights in column (1), and the weighted sum of the ratio of R&D-to-production in the upstream industries with input coefficients as weights in column (2). The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

2.6 Conclusion

I build a theoretical framework based on the concept of complementarity in technology shift in Chapter 1. In the framework, I posit that human capital serves as an adoption good for modern technology which is less unskilled labor-intensive and more intermediate goods-intensive. Modern technology is skilled labor-intensive since it needs human capital as an adoption good, and is also capital-intensive since firms will adopt advanced or automated machinery to depend less on unskilled workers and convert intermediate inputs into more output products.

When industries that supply intermediate goods increase their human capital accumulation (when there are more outside adopters of modern technology), a firm will gain more if it hires skilled workers and adopt modern technology, because intermediate inputs become cheaper and the benefit of intermediate inputs is maximized under modern technology which is intermediate goods-intensive. I provide empirical evidence that the increase of outside human capital accumulation due to the expansion of the college enrollment quota promotes a technology shift toward more capital-intensive and skilled labor-intensive but less unskilled labor-intensive. The specific role of human capital as an adoption good for modern technology, however, remains unsolved. Candidates of the specific role of human capital would be to conduct R&D to develop modern technology and/or assimilate modern technology developed outside the firm; to operate imported machinery and equipment with modern technology; or to promote trade to import advanced intermediate goods and capital goods.

I focus on R&D in this paper. Human capital is rivalrous and a worker cannot be hired by more than one firm simultaneously. A firm, however, can hire rivalrous human capital to carry out R&D. The result of R&D, knowledge, is non-rivalrous and the effect of knowledge can spill over to other firms. Furthermore, many contributions to literature regarding R&D point out that a firm's own R&D not only generates knowledge but also facilitates assimilation of knowledge developed elsewhere. This is so-called absorptive capacity: the effect of R&D spillover is increasing in a firm's own R&D. Absorptive capacity supports the concept of complementarity – the effect of own R&D is increasing in R&D spillover – since both concepts, absorptive capacity and complementarity, are the two sides of the same coin.

The results in this paper are as follows: First, I find that human capital accumulation leads to an increase in a firm's R&D spending. To be specific, human capital accumulation in the upstream supplier industries promotes positive relationship between a firm's skilled-to-unskilled labor ratio and total R&D spending. Second, I find that the effect of R&D spillover on the firm's profit is increasing in its own R&D, in most specifications. This finding confirms not only that R&D serves as a measure of a firm's absorptive capacity, but also that complementarity in technology adoption holds. Third, I provide evidence that outside R&D increases a firm's capital productivity. Specifically, a one standard deviation increase in *spillover* leads to 4.71-4.77 percent increase from the baseline capital productivity with zero *spillover*. On the other hand, elasticity of skilled labor is revealed to be decreasing and that of unskilled labor is increasing in outside R&D, which are contrary to the theoretical prediction. The gap between theoretical prediction and empirical result might be a consequence of structural phenomena not included in the model, such as international R&D spillover, importing tech-embedded advanced machinery, or exporting capital-intensive goods. Future studies exploring such roles of human capital would fill the gap this paper left behind.

The contribution of my paper is first, that I connect the concept of complementarity and absorptive capacity of R&D to show that there can be multiple equilibria and that the government policy of promoting human capital accumulation can result in landing on the desirable equilibrium. Second, I connect two main streams of aggregate growth theory: assimilation and accumulation. I use R&D as a key driver of growth as the new growth theory (assimilation view) suggests, but instead of TFP growth, I verify the effect of R&D spillover on the adoption of new, more productive technology that is physical capital-intensive. As firms' production technology shifts toward more capital-intensive methods, it can delay diminishing returns on capital.

Until now, I specify human capital in the skilled ("white-collar") – unskilled ("blue-collar") labor dimensions, but it can also be defined in the permanent – temporary labor dimensions. Using temporary workers can be regarded as negative human capital accumulation since temporary workers are less educated and have less chance of being trained by employers. The ratio of permanent-to-total labor, hence, can serve as a measure of human capital accumulation as well. In the next paper, I explore the theory explaining the channels through which the use of temporary workers affects labor productivity, and explain a diverging trend between permanent and temporary employment by using the concept of complementarity in permanent employment.

Chapter 3

Labor Productivity, Complementarity, and Diverging Trend of Employment between Permanent and Temporary Workers

3.1 Introduction

In the previous two chapters, I use a dimension of skilled (white-collar) and unskilled (blue-collar) labor to analyze human capital accumulation and its impact on the development process during the 1980s and 1990s in South Korea. In Chapter 1, I verify that in the 1980s and 1990s there is complementarity in technology adoption. In other words, more adopters industry-wide increase a marginal adopter's gain. When complementarity exists in technology adoption, there could be multiple equilibria and a coordination failure could result in an economy stuck in an unfavorable equilibrium of traditional technology. In that paper, I construct a model to show how expansion of the college enrollment quota and a subsequent increase in human capital accumulation provided a Big Push for a specific firm to adopt modern capital-intensive technology. I go on to provide empirical evidence that outside human capital accumulation, as measured by a weighted sum of ratios of skilled-to-unskilled workers in the upstream industries with input coefficients as weights, promotes a firm's technology shift toward capital-intensive production techniques. In Chapter 2, I verify the specific role of human capital in the process of a technology shift in the same period of the 1980s and 1990s in South Korea. I focus on Research and Development (R&D) and its property of absorptive capacity[54] which justify complementarity[55] in R&D activity. I verify that (i) human capital accumulation in the upstream industries increases a firm's R&D activity; (ii) a firm's R&D has the property of absorptive capacity, and hence, there is complementarity in R&D activity; and (iii) R&D spillovers facilitate a firm's technology shift toward capital-intensity.

In this chapter I use another dimension of human capital, permanent and temporary labor, and focus on explaining the phenomenon of diverging employment between the two in the 2010s. Temporary workers are those who are hired with a fixed-term contract (fixed-term contract workers), or those who are hired by an agency and dispatched to a firm (temporary agency workers). These types of workers are distinguished from permanent (or regular) workers by wages and job security. In the 1990s and 2000s, the fraction[56] of permanent workers in all industry in South Korea remained steady at between 50% and 60%. The ratio decreased at the

[54] The effect of R&D spillover is increasing in a firm's own R&D.
[55] The effect of a firm's own R&D is increasing in R&D spillover.
[56] $Permanent\ ratio = \frac{Permanent\ workers}{Temporary\ workers + Permanent\ workers}$

time of the Asian Financial Crisis. The government at that time tried to alleviate labor market rigidity by allowing employers to use temporary agency workers, and to lay off their employee for managerial needs. As a result, the number of permanent workers decreased while that of temporary workers increased to exceed the number of permanent workers, and so the permanent ratio fell below 50% (48~49% between 1999 and 2002).

Even though the permanent ratio soon recovered to its pre-crisis level, there has been a long debate on temporary employment. One group argues that temporary workers are less paid and trained while taking more risk of losing job than permanent workers, so they should be more protected. The other group, however, argues that the protection for temporary employment would put restriction on business activities and raise the problem of unemployment again. After a long debate, the Korean government implemented Temporary Employment Protection Legislation (EPL) in 2007. The law imposes a restriction on employers that they cannot hire the same temporary workers for more than two years unless converting their status to permanent. After the implementation of temporary EPL, the number of temporary workers began to decrease while that of permanent workers kept increasing. The percentage of permanent workers rose 60% in 2011, and has continued to increase. Ten years later, the permanent worker ratio reached 70%.

To understand the continued increase of the permanent worker ratio in South Korea in the 2010s, I focus on the effect of a firm's temporary employment on its labor productivity in manufacturing industries to see whether the merits of temporary employment still exist after implementation of the temporary EPL. Theories on this subject take two opposite views. The "human capital" and "spillover to permanent workers" view predicts that temporary workers negatively affect labor productivity. Temporary workers can be a downgrade of human capital for firms since they tend to be less educated and because employers have less incentive to offer job training for temporary workers. Also, if temporary employees become a majority in the firm, this situation will negatively affect permanent workers and reduce labor productivity. For example, an increase in temporary employment could worsen relations among employees or threaten permanent workers and their job status (George, 2003; Kraimer et al., 2005; Broschak and Davis-Blake, 2006). The opposing view stresses “flexibility” and “screening” and claims that temporary workers positively affect labor productivity. Temporary workers could meet the employer’s need for flexibility and screening purposes. Employers could easily hire and fire temporary workers to address demand shocks and have a probation period to determine which workers are productive (Hirsch and Mueller, 2012). Based on of these contradictory theoretical views, I examine empirical evidence of temporary workers’ effect on labor productivity in a specific context. The implementation of the temporary EPL in 2007 seems to impair the flexibility and screening purpose of temporary employment. The two-year rule prevents employers from flexible use of temporary workers, and also damages screening purpose since employers usually respond to lay off temporary workers every two years.

In this paper I examine the general effect of temporary employment on labor productivity. Then, I use quadratic terms of temporary employment to analyze the effect through each channel, because effects through flexibility and screening are supposedly maximized at the initial level of temporary employment, while the effect through spillover to permanent workers increases with the level of temporary employment. I find an overall negative effect of temporary workers on labor productivity. As predicted, the positive effects through flexibility and screening are overwhelmed by the negative effect through (low) human capital. It gives a clue to understand a diverging trend between permanent and temporary workers.

However, verifying the effect of temporary employment on labor productivity alone does not fully explain the continued trend of a diverging trend and the subsequent increase in permanent ratio. Considering the supply and demand in the labor market with a price mechanism as an invisible hand, it needs more rational to explain the continued divergence trend between permanent and temporary employment. I try to explain this by adopting the concept of complementarity in permanent employment. If there exists complementarity in permanent employment, the better it is for a firm to hire permanent employment. It is reasonable since I verify that the increase in a firm's temporary-to-permanent ratio decrease the firm's labor productivity. Hiring permanent employment, however, is relatively expensive compared to temporary workers. If other firms do not increase much in permanent employment, it is worse for a firm to increase permanent employment. Implementation of temporary EPL could be a trigger like a Big Push to breakthrough this situation. The implementation of the legislation makes firms believe that other firms will hire permanent workers rather than temporary workers due to the regulation on temporary employment, and so a firm increases its permanent employment to get more benefit. I examine whether there is complementarity in permanent employment in manufacturing in the 2010s. I construct a spillover variable which is the weighted sum of permanent ratio in the upstream industries with input coefficients as weights and I go on to interact the spillover variable with a firm's permanent ratio. I find that more permanent employment in the upstream industries increase profit and investment of a firm hiring permanent workers. Hence, the result support the explanation for the divergence in employment of permanent and temporary workers. It verifies that there is complementarity in permanent employment, and the result implies that temporary EPL serves as a big push to trigger continuously increasing trend of permanent employment since the merit of temporary employment are outweighed by the demerit of low human capital in temporary employment in the 2010s.

I go on to draw an implication from the concept of complementarity that is examined in each chapter. Chapter 1 verifies that complementarity existed in hiring skilled workers in South Korea between 1982 and 1996. When complementarity exists at the early stage of development process, only a few firms hire skilled labor. Others are discouraged from hiring skilled labor because the fewer the firms that do it, the worse it is for a specific firm to do it. Hence, the country could have become stuck in and underdeveloped state. In South Korea, however, expanded college enrollment served as a Big Push. As the supply of skilled workers in the manufacturing industries increased, more firms hired skilled labor because they expected other firms to do so.

Chapter 2 verifies that complementarity in R&D existed in South Korea between 1982 and 1996. However, complementarity in R&D no longer worked between 2015 and 2019. In other words, in these more recent years, the more firms do R&D, the worse it is for a specific firm to do R&D. Recent studies indicate that R&D spillovers from the adjacent technological space become more important than the supply chain as a country is closer to a technological frontier (Aldeiri et al., 2018), and that a firm has more likely to reduce R&D if the R&D results spill over more to its rivals (Arora et al., 2020). If complementarity does not exist, a Big Push-type policy will not work well. Rather, policy makers should change the incentive structure to encourage complementarity in R&D activity. An example of this type of policy is a system in which gain from outside knowledge is shared with its creator.

This chapter makes two contributions. First, it provides empirical evidence for theories that explain the effect of temporary workers on labor productivity. In the specific context of

South Korea, the negative effect of human capital outweighs positive effects through flexibility and screening. Second, this paper explains diverging trend between permanent and temporary employment after temporary EPL was implemented by using the concept of complementarity in permanent employment. Furthermore, this paper verifies that permanent employment in the upstream industries promote a firm's technology shift from capital-intensive toward permanent labor-intensive, which is adverse for the country's economic growth by fortifying diminishing returns on capital.

This paper is organized as follows. Section 3.2 reviews the relevant literature. Section 3.3 describes the case of South Korea. Section 3.4 describes the data and Section 3.5 presents the specifications. Section 3.6 concludes the chapter.

3.2 Literature Review

3.2.1 Theories about how temporary workers affect labor productivity

Employment Protection Legislation (EPL) and the resulting rigidity of the labor market, such as the high cost of firing permanent workers, are major causes of unemployment in Europe (Bertola, 1990; Cahuc and Postel-Vinay, 2002). To address the problem of unemployment, European countries allowed firms to hire temporary workers with fixed-term contracts so that the firms could increase their employment with less firing cost (Booth, Francesconi, and Frank, 2002). The same approach was adopted in South Korea. After the Asian Financial Crisis in 1997 and the subsequent increase in unemployment, the country changed its policy to allow firms to lay off their workers by managerial needs, and to hire temporary agency workers. The policy change was intended to reduce unemployment because temporary workers are paid less wages with almost no fringe benefits and incur fewer firing costs than permanent workers. The government assumed that temporary workers would resolve unemployment without affecting the labor productivity of firms adopting temporary workers (Vergeer and Kleinknecht, 2014; Lisi and Malo, 2017). Two schools of thought exist about how temporary workers affect labor productivity: some theories posit that temporary workers increase labor productivity by allowing increased flexibility and better screening of potential employees, while others maintain that temporary workers decrease labor productivity because temporary workers are less valuable as human capital and the effects of hiring temporary workers spill over to permanent workers.

3.2.1.1 The positive effect through channels of flexibility and screening

Temporary workers cost less to fire than permanent workers do, so firms can easily hire temporary workers without worrying that they will not be able to handle changes in demand for their products (Bentolia and Saint-Paul, 1992; Goux et al., 2001). Empirical evidence suggests that stricter EPLs (for permanent workers) increase the use of temporary workers (Booth, Dolado, and Frank, 2002; Nunziata and Steffolani, 2007; Shire et al, 2009). With stricter protection of permanent workers, the relative cost of firing temporary workers is lower, and hence, employment of temporary workers is higher. Since firms can respond to increased demand for their product by hiring temporary workers, these types of workers help firms avoid underutilizing capital and/or labor, and hence, hiring temporary workers increases labor productivity (Hirsch and Mueller, 2012).

Fixed-term contract also help firms screen potential employees in order to select better and deter worse workers. Research shows that temporary workers put more effort into the probation period and show more productivity after converting to permanent workers (Wang and

Weiss, 1988). Temporary employment can be a stepping stone to regular employment: temporary workers have a greater chance of being hired for permanent jobs than do the unemployed (Kvasnicka, 2009). Temporary work thus provides an incentive for temporary workers to exert more effort than permanent workers. This conjecture is supported by evidence that temporary workers work more unpaid overtime than do permanent workers (Engellardt and Riphahn, 2005), and that absenteeism increases with higher levels of labor protection (Ichino and Riphahn, 2005). Beckmann and Kuhn (2009) compare temporary workers' effect on labor productivity through the channels of flexibility and screening. They conclude that firms using temporary workers as stepping stones to regular employment are more productive than firms using temporary workers to satisfy the demand for flexible employment. Meanwhile, Autor (2001) finds that free general skill training for temporary agency workers can increase their productivity because this training serves as both a screening method for the agency firm and a self-selection mechanism for agency workers.

3.2.1.2 The negative effect through channels of human capital and spillover

Temporary workers in general are less educated than permanent workers. Temporary workers are paid less and receive lower fringe benefits than permanent workers. This wage gap between temporary and permanent workers could be based on differences in education, experience, and/or occupation (Nollen, 1996; Garz, 2013). Nollen (1996) finds that the proportion of college graduates is 7 percentage points lower for temporary agency workers in the US than for permanent workers. This difference means that less-educated workers are more likely to become temporary workers and that hiring temporary workers may lower labor productivity because they are less valuable as human capital. However, educational level does not fully explain the wage gap between temporary and permanent workers. The unexplained part of the wage gap can be thought of as a wage penalty for temporary workers (Forde and Slater, 2005). Vergeer and Kleinknecht (2014) find that hiring temporary workers as a cheaper form of labor negatively affects labor productivity.

In addition, employers have less incentive to offer job training to temporary workers and temporary workers have less incentive to take it. Theory suggests a trade-off between training and flexibility (Arulampalam and Booth, 1998). Since employer-funded training incurs an up-front cost for a later benefit and temporary workers have fixed-term contracts, employers have less incentive to give temporary workers job training to equip firm-specific human capital. For the same reason, temporary workers have less incentive to gain firm-specific human capital and are more likely to get general human capital (Nollen 1996). Nollen (1996) finds that temporary workers have 12-20% less training for males and 7-15% less for females than do permanent workers. Some studies find less employer-funded training for temporary workers than for permanent workers (Draca and Green, 2004; Kauhanen and Natti, 2015). On the other hand, Forrier and Sels (2003) and Fouarge et al. (2012) find that temporary workers are willing to fill the employer-funded training gap through own in investment in training, but the gap is only partially filled. In short, although temporary workers may be eager to build firm-specific human capital, they have less chance to do so than permanent workers. As a result, hiring temporary workers may result in lower labor productivity. It is worth mentioning again that temporary agencies can help improve human capital as well as self-selection and screening by offering training for their agency workers (Autor, 2001).

Temporary workers can also have negative spillover effects on permanent workers. When firms are initially allowed to hire temporary workers, these fixed-term workers represent only a small portion of the employees. However, the permanent workers may suffer when the number of temporary workers increase (George, 2003; Hirsch and Mueller, 2012). Some empirical evidence suggests a negative spillover effect. Temporary workers hurt permanent workers' commitment and increase regular workers' willingness to quit their job (George, 2003; Broshak and Davis-Blake, 2006). Kraimer et al. (2005) find that permanent workers who are less secure are more likely to consider temporary workers as a threat to their position, and this perception leads to lower job performance. However, some researchers argue that temporary workers can spur permanent workers to improve their performance (Bryson, 2007).

3.2.2 Empirical evidence of temporary workers on labor productivity

So far, two streams of theories predict opposite effects of temporary workers on the firm's labor productivity. Temporary workers can positively affect labor productivity by allowing greater flexibility and better screening, but negatively affect it through reduced human capital and spillover to permanent workers. Reviewing empirical evidence gives an insight for constructing a model to examine the effect through each channel.

3.2.2.1 Negative effect on labor productivity

Many studies find empirical evidence that temporary workers adversely affect labor productivity. Labor productivity decreases when changes in labor policy allow firms to hire temporary workers (Cappellari et al., 2012; Boeri and Garibaldi, 2007). Also, labor productivity decreases according to the proportion of temporary workers in a firm (Ortego and Marchante, 2010; Lisi, 2013; Lucidi and Kleinknecht, 2010). The negative effect of temporary workers is more severe in specific conditions: temporary workers are more likely to decrease labor productivity when firm-specific knowledge is important to the innovation process (Kleinknecht et al., 2014) or when firms are in the skill-intensive sectors (Lisi and Malo, 2017). Furthermore, some evidence suggests that reducing wage costs by hiring temporary workers also reduces labor productivity (Vergeer and Kleinknecht, 2010).

3.2.2.2 Inverse U-Shaped effect / No effect

Some studies find that the effect of temporary workers on labor productivity is initially positive and turns negative as the proportion of temporary workers increases (Beckmann and Kuhn, 2009; Hirsch and Mueller, 2012; Nielen and Schiersch, 2014[57]). In the early stage when a firm has only a few temporary workers, the temporary workers will positively affect labor productivity through the channel of screening because they will work hard to gain permanent employment. As the proportion of temporary workers increases, however, permanent workers perceive temporary workers as a threat to their own jobs, leading to decreased labor productivity. In other words, the ratio of temporary workers and labor productivity may have an inverse U-shaped relationship.

A few studies find that fixed-term contracts do not affect labor productivity (Nielen and Schiersch, 2016), and that temporary workers do not impact investing in R&D[58] if general knowledge matters in the innovation process (Kleinknecht et al., 2014).

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[57] Nielen and Schiersch (2014) find an inverse U-Shaped relationship between temporary agency work and firm competitiveness. However, Nielen and Schiersch (2016) find no significant effect of fixed-term contracts on labor productivity.

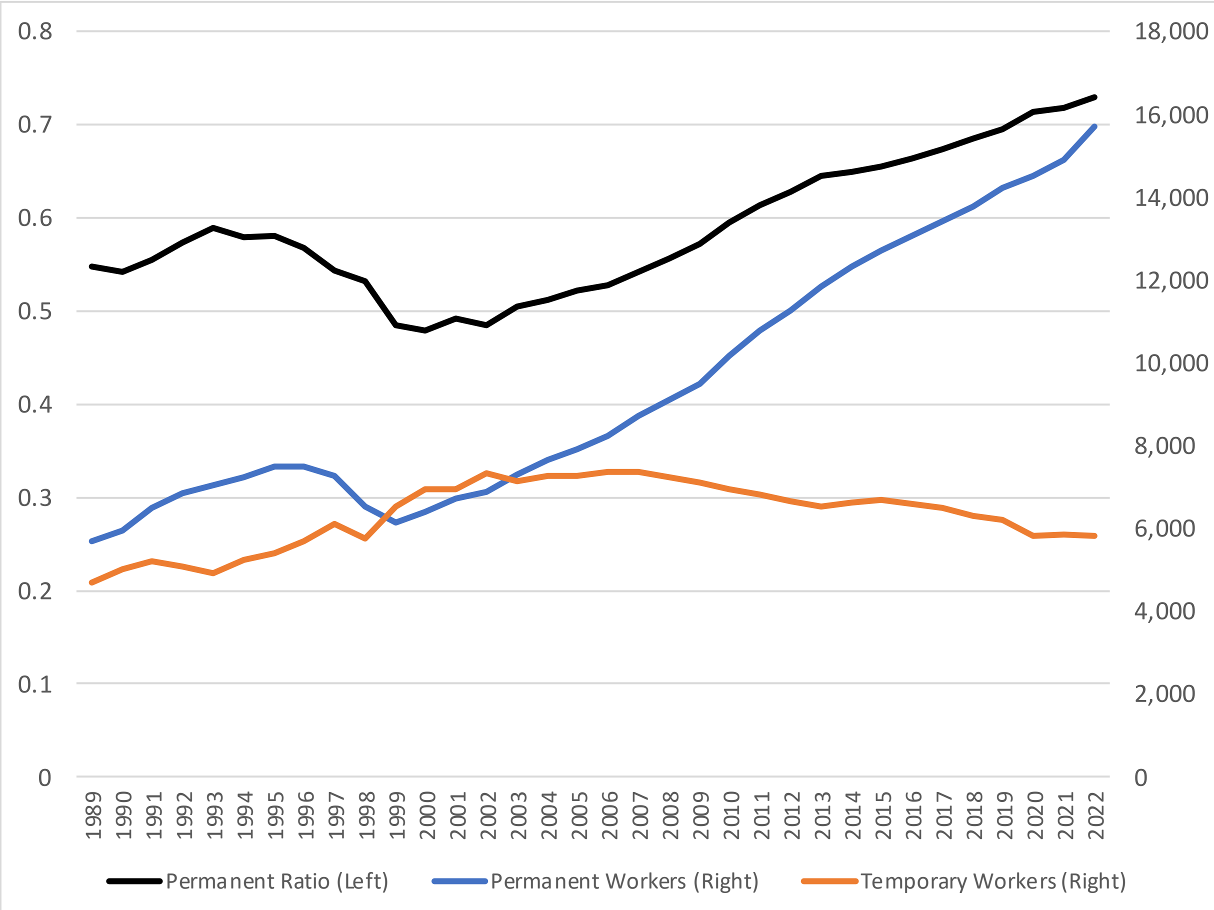
[58] However, they find that temporary employment has a negative effect on a firm's R&D if firm-specific knowledge matters in the innovation process.

3.3 The Context of South Korea

3.3.1 Background of Temporary Employment Protection Legislation in South Korea

South Korea experienced rapid economic growth through a government-led export-oriented approach in the 1960s and 1970s, leading Heavy Chemical Industries to became competitive in the world market. The government later moved toward a market-oriented approach. Employees were, however, still strongly protected and a majority of employees enjoyed lifetime employment. As economic growth slowed down in the middle of the 1990s and the Asian Financial Crisis of 1997 damaged the country, many firms went bankrupt and unemployment became prevalent. To reduce unemployment, the government alleviated rigidity in the labor market by allowing firms to lay off their employees based on managerial needs and by allowing firms to use temporary agency workers (Yoo and Kang, 2012). The economic crisis and the subsequent change in labor policy resulted in a decrease in permanent workers and an increase in temporary workers. The fraction of permanent workers in all wage workers fell below 50%, meaning that the number of temporary workers exceeded that of permanent workers in all industries. As the number of temporary workers increased, so too did controversies over temporary employment. Firms could hire temporary workers for a fixed term and freely lay them off when it ended. Furthermore, the government did not restrict the duration of temporary employment at first: firms could hire temporary workers and keep them temporary, with the option of either renewing or laying them off at the end of every contract period. However, temporary workers were at a risk of being laid off when the contract ended. Advocates for workers' rights, therefore, argued that there should be more protection for the temporary workers.

Figure 3.1: Permanent Ratio, Number of Permanent and Temporary Workers (in thousands)



Source: Economically Active Population Survey, Statistics Korea (2022)

To protect temporary workers from this job status uncertainty, the Korean government implemented temporary Employment Protection Law (EPL)[59] which limited firms to hiring temporary workers for no more than two years. After two years, they must hire temporary workers permanently. The two-year rule went into effect on July 1, 2007. Firms which already had temporary workers had two years from this date to permanently hire.

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[59] The Act on the Protection of Fixed-term and Part-time Employees and the Act on the Protection of Dispatched Employees.

3.3.2 Divergence in the Employment of Permanent and Temporary Workers

After the implementation of EPL, labor market in South Korea experienced a divergence in the number of workers between permanent and temporary. The proportion of permanent workers has maintained between 50 and 60 percent in the 1990s and 2000s as shown in Figure 3.1. Even when the Asian Financial Crisis occurred and the government tried to alleviate labor market rigidity by allowing firms to lay off their employee by the managerial needs and to use temporary agency workers, the ratio only slightly go below 50 percent and it went back to a range between 50 and 60 percent a few years later. After 2007 when the temporary EPL implemented, the number of temporary workers began to shrink while that of permanent employment continued to increase. As a result, the ratio of permanent employment exceeds (61.3%) in 2011, and the ratio continued to increase and went beyond 70 percent (71.4%) in 2020. To explain why there has been a divergence in employment between permanent and temporary workers, I focus on the two roles of temporary EPL in 2007. First, the temporary EPL weakened the flexibility and screening purpose of temporary employment. Firms are restricted to use the same temporary workers for only two years unless they convert temporary workers to permanent workers, and it lessened firm’s flexibility upon temporary employment. They usually responded to the restriction by laying off temporary workers every two years, and it led to a damage to the screening purpose of temporary employment. I examine the effect of temporary employment on labor productivity to verify whether these two channels are outweighed by the channel of human capital even at the stage of low temporary ratio. Second, temporary EPL can serve as a Big Push. After the implementation of temporary EPL, firms may expect other firms will increase permanent employment since hiring temporary workers lose its merits on flexibility and screening. If there exists complementarity in permanent employment, i.e., the effect of a firm's permanent employment on its profit is increasing in permanent employment in the upstream industries, implementation of temporary EPL can trigger divergent employment between permanent and temporary workers.

3.3.3 Which theoretical channel is dominant after temporary EPL in South Korea?

Baek and Park (2018) show that the temporary EPL implemented in 2007 reduced temporary employment but that only a fraction of temporary workers became permanent workers. The law thus had an unintended outcome of temporary workers being laid off within two years. I conjecture this change weaken the positive effect of screening because temporary workers have an increased chance of being laid off rather than being converted to permanent workers. But as temporary workers have less chance to become a majority in a firm, the negative effect of spillover to permanent workers is weakened as well. The positive effect of flexibility also decreases after the EPL implementation because the cost of hiring temporary workers increases. The act reduces the chance of on-the-job training for temporary workers and strengthens the channel of human capital. Hence, I hypothesize that temporary workers in South Korea lower a firm's labor productivity mainly because they are less valuable as human capital, and they have marginal effects through the channels of flexibility, screening, and spillover to permanent workers. I examine whether screening and flexibility effects are outweighed by human capital effects even at the low level of temporary ratio by adopting quadratic terms in the model.

3.4 Data

I use plant-level panel data between 2011 and 2019 from Mining and Manufacturing Survey (MMS) data to verify temporary workers' effect on a firm's labor productivity. The MMS data is based on a yearly census by Statistics Korea. It includes development outcomes like production, value-added, investment, and profit, and it also shows the number of permanent and temporary workers in each plant. Notably, the MMS recorded the number of blue-collar and white-collar workers until 2006, but in 2007, it changed its categories of workers and started to record the number of temporary and permanent workers. Hence, the number of temporary (and permanent) workers is available from 2007 in the MMS data. I choose, however, not to use the years from 2007 to 2009[60] in the analysis. First, I do not want the analysis to be skewed by the effect of the global financial crisis which began in late 2007 and lasted for two to three years. Second, I want to keep the level of firm-specific human capital in each temporary worker constant during the period of analysis. The labor reform implemented on July 1, 2007, limited firms to hiring the same temporary workers for more than two years unless the firms convert them to permanent workers. Therefore, temporary workers hired after the new reform must be hired as permanent workers or laid off after two years. However, temporary workers who were already hired before July 1, 2007, could be kept as temporary workers for two years past that date. As a result, between 2007 and 2009, a firm could have temporary workers who had worked for more than two years. After 2009, the firm would only have temporary workers who had been there less than two years. Employees who had been at the same firm for more than two years could have more firm-specific human capital. To limit the analysis to temporary workers who have worked at the same firm for less than two years, I use data from between 2011-2019.

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[60] I also choose not to use 2010 data since there is no data for capital such as building and structure, machinery and equipment, and vehicles in the MMS data.

This paper uses the same data-cleaning procedures applied to the previous papers. I use a capital deflator for each type of capital formation – building and structure, machinery and equipment, and vehicles – to convert nominal values of capital and investment to real values. Also, I use the industry-level Producer Price Index to get real values of production, value-added, profit, R&D, and sales. MMS data with different industrial codes[61] are harmonized to the 9th Korean Standard Industry Code (KSIC), and again, industries used in the IO table are harmonized with those in MMS data to connect each other.

[61] MMS in 2007-2015 are based on KSIC 9th, and MMS after 2015 are based on KSIC 10th.

Table 3.1: Descriptive Statistics

	[2011-2019]	2011	2012	2013	2014
# Firms	605,685	62,955	63,728	65,269	68,428
Permanent labor	39.5975	39.5383	39.7785	39.7984	39.2738
	(250.9169)	(257.4765)	(248.3041)	(247.4054)	(240.4561)
Temporary labor	1.7448	2.3711	2.1671	1.9547	1.7325
	(12.3169)	(11.1789)	(10.2268)	(8.0568)	(7.3996)
Capital	5243.942	5368.579	5262.914	5471.536	5428.431
	(112728.4)	(99298.71)	(97580.21)	(108278.7)	(113212.4)
Temp ratio[62]	0.2146	0.2923	0.2614	0.2388	0.2254
	(1.3894)	(1.5492)	(1.4381)	(1.3671)	(1.2372)
Perm ratio[63]	0.9289	0.9047	0.9107	0.9180	0.9211
	(0.1807)	(0.2097)	(0.1993)	(0.1914)	(0.1898)
Forward[64]	0.6723	0.6706	0.6676	0.6716	0.6724
	(0.1577)	(0.1568)	(0.1558)	(0.1558)	(0.1561)
Investment	937.0221	1223.383	968.6705	945.6708	978.4593
	(35240.92)	(39649.57)	(29666.83)	(27283.08)	(30500.01)
Profit	7654.099	6362.198	6473.923	6264.304	7652.684
	(165401.8)	(122060.8)	(128949.8)	(126551.5)	(136331.1)
Price	100.7553	100.9906	101.7762	101.1433	101.4428
	(6.8369)	(11.4568)	(8.8006)	(6.4551)	(4.0320)
Industry-level controls					
Production-Capital ratio	5.5323	5.6429	5.5753	5.3720	5.0628
	(8.7868)	(3.5108)	(3.3983)	(3.1352)	(2.6733)
Production-Labor ratio	352.4758	352.1794	347.9843	345.6993	341.181
	(303.5103)	(301.9083)	(299.625)	(302.2339)	(289.7621)
Value added-Production ratio	0.3828	0.3658	0.3685	0.3683	0.3761
	(0.0978)	(0.0946)	(0.0975)	(0.0970)	(0.0967)
Profit-Production ratio	0.3123	0.2707	0.2797	0.2769	0.3109
	(0.1383)	(0.1746)	(0.1722)	(0.1691)	(0.1103)
Profit-Sales ratio	0.2582	0.0110	0.1326	0.1176	0.3338
	(0.9310)	(2.0313)	(1.1384)	(1.1662)	(0.1199)

62 $Temp\ ratio = \left(\frac{Temporary}{Permanent}\right)_{ijt}$

63 $Perm\ ratio = \left(\frac{Permanent}{Temporary+Permanent}\right)_{ijt}$

64 $Forward = \sum_k \alpha_{ki} \left(\frac{Permanent}{Temporary+Permanent}\right)_{kt}$

Table 3.1: Descriptive Statistics, continued

	[2015-2019]	2015	2016	2017	2018	2019
# Firms	345,305	68,911	68,547	69,182	69,266	69,399
Permanent labor	39.6011	39.5714	39.9186	39.6357	39.7163	39.1675
	(252.8678)	(256.1591)	(246.209)	(250.9675)	(252.3351)	(258.4325)
Temporary labor	1.5155	1.8293	1.6538	1.4579	1.3427	1.2952
	(14.1679)	(20.5876)	(11.4659)	(12.4238)	(12.3161)	(11.9409)
Capital	5138.138	2933.436	5512.739	5665.151	5857.884	5713.605
	(118192.1)	(71178.41)	(114755.6)	(126892.1)	(134259.5)	(131989.3)
Temp ratio	0.1852	0.2284	0.1944	0.1742	0.1697	0.1595
	(1.3655)	(1.4691)	(1.5124)	(1.2077)	(1.2987)	(1.3175)
Perm ratio	0.9403	0.9278	0.9358	0.9424	0.9466	0.9488
	(0.1659)	(0.1810)	(0.1718)	(0.1630)	(0.1574)	(0.1544)
Forward	0.6737	0.6734	0.6730	0.6746	0.6731	0.6744
	(0.1589)	(0.1579)	(0.1585)	(0.1589)	(0.1595)	(0.1597)
Investment	869.1266	547.9722	915.8595	977.4421	989.5865	913.6577
	(37474.03)	(27385.8)	(35091.29)	(43936.36)	(42955.89)	(35499.81)
Profit	8513.8	8121.137	8596.222	8538.778	8596.092	8707.02
	(191673.4)	(147163.2)	(172360.5)	(179028)	(201096.8)	(242831.7)
Price	100.3143	100	98.7972	100.1515	101.2693	101.3342
	(5.6700)	(0)	(3.5751)	(6.0169)	(7.3775)	(7.2509)
Industry-level controls						
Production-Capital ratio	5.6360	7.9648	5.1159	5.0802	5.0279	4.9981
	(11.3008)	(5.1159)	(2.6231)	(2.4530)	(2.5522)	(2.3531)
Production-Labor ratio	356.8778	346.3107	352.426	359.8259	360.5652	365.1488
	(307.3016)	(295.8269)	(312.9666)	(307.8084)	(306.7644)	(312.4717)
Value added-Production ratio	0.3926	0.3905	0.3939	0.3912	0.3921	0.3953
	(0.0976)	(0.0951)	(0.0971)	(0.0978)	(0.0997)	(0.0982)
Profit-Production ratio	0.3329	0.3296	0.3344	0.3319	0.3302	0.3383
	(0.1162)	(0.1106)	(0.1160)	(0.1158)	(0.1207)	(0.1176)
Profit-Sales ratio	0.3381	0.3596	0.3500	0.3483	0.2804	0.3524
	(0.4929)	(0.0954)	(0.1562)	(0.1546)	(1.0556)	(0.1935)

3.5 Specification

As mentioned above, two schools of thought exist about temporary workers' effect on labor productivity. Some theories predict that temporary workers positively affect labor productivity through flexibility and screening, while others predict that they negatively affect labor productivity through human capital and spillover. My strategy is to examine (i) the general effect of temporary workers and (ii) the effect from each channel by adopting square terms of the temporary-permanent workers ratio.

3.5.1 The overall effect of temporary employment

To examine the effect of temporary employment on a firm's labor productivity, I construct a model by taking a log on Cobb-Douglas production function and interacting logged inputs with a ratio of temporary-to-permanent labor. I estimate the model

(3.1) $Y_{ijt} = X'_{ijt}\beta + (Temporary\ ratio)_{ijt}X'_{ijt}\gamma + \alpha_j + \delta_t + \varepsilon_{ijt}$

where Y_{ijt} is a log of value-added[65] and X_{ijt} is a vector of logged inputs (labor[66] and capital), and $Temporary\ ratio_{ijt}$ is the ratio of temporary-to-permanent labor (hereafter *tempratio*) in firm *j* in industry *i* in time *t*. The variables α_j and δ_t refer to firm- and year-fixed effect, respectively. The error term ε_{ijt} represents unobservable characteristics. Standard errors are clustered at a firm level. Since unobserved productivity shock in the error term ε_{ijt} could be correlated with (logged) inputs and value-added, I use the Levinsohn-Petrin[67] (LP) method to resolve this endogeneity problem in Equation (3.1). Also, a confounder could exist in the error term ε_{ijt} that

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[65] Value-added is the value of production minus intermediate inputs used for production.
[66] Labor is the sum of permanent and temporary workers.
[67] Levinsohn-Petrin (2003) use intermediate inputs as proxies for unobserved productivity shock. Their method resolves the problem of zero-investment in nontrivial number of firms in Olley-Pakes (1996) that use investment as a proxy.

is correlated with *tempratio* and value-added (in log). I adopt one- and two-year lagged[68] *tempratio* as instrumental variables for the current *tempratio.* It is less likely that a confounder exists that is effective more than one year and affects both lagged instruments and the current value-added. Hence, the instruments are exogenous to a confounder in the current error term. Furthermore, instruments of one- and two-year lagged *tempratio* is likely to be relevant to an endogenous regressor of current *tempratio* since a firm's number of employee may not fluctuate overtime. First stage regressions are given by

(3.2) $$(Temporary\ ratio)_{ijt} = X'_{ijt}b + Z^{t-1}_{ijt-2}X'_{ijt}c + \alpha_j + \delta_t + \varepsilon_{ijt}$$

$$(Temporary\ ratio)_{ijt}X_{1,ijt} = X'_{ijt}b_1 + Z^{t-1}_{ijt-2}X'_{ijt}c_1 + \alpha_{1,j} + \delta_{1,t} + \varepsilon_{1,ijt}$$

$$\vdots$$

$$(Temporary\ ratio)_{ijt}X_{n,ijt} = X'_{ijt}b_n + Z^{t-1}_{ijt-2}X'_{ijt}c_n + \alpha_{n,j} + \delta_{n,t} + \varepsilon_{n,ijt}$$

where Z^{t-1}_{ijt-2} is a vector of one- and two-year lagged *tempratio* and *n* is the number of input factors, and thus X_1 represents labor (in log) and X_2 represents capital (in log). The remainder of the notation is the same as in Equation (3.1).

Table 3.2 presents the results from estimating Equation (3.1). All columns include firm- and year-fixed effects. Column 2 uses instruments while column 3 uses the LP method to address possible endogeneity in Equation (3.1). Column 2 (FE+IV) and column 3 (FE+LP) show a negative coefficient on interaction variable of *Log (Labor) * tempratio*, which indicates that a firm's temporary employment decreases its labor productivity. On the other hand, column 1 (FE) show a positive coefficient on the same variable, which indicates that temporary employment

[68] Besley and Burgess (2000) adopt lagged variable as instrumental variable. They choose instrumental variable of political group in year *t-8* for the regressor of cumulative land reform in year *t-4* and the dependent variable of poverty in year *t*.

increases a firm's labor productivity. Meanwhile, all regressions show that temporary employment reduces a firm's capital productivity.

Table 3.2: General Effect of *tempratio* on Labor Productivity

Log (Value-added)	(1) FE	(2) FE+IV	(3) FE+LP
Log (Labor)	0.6724***	0.6556***	0.4291
	(0.0047)	(0.0090)	(0.0487)
Log (Capital)	0.0827***	0.0701***	0.0903
	(0.0016)	(0.0021)	(0.0209)
Log (Labor)	0.0037	-0.0999**	-0.0068
** tempratio*	(0.0031)	(0.0417)	(0.0333)
Log (Capital)	-0.0055***	-0.0007	-0.0051
** tempratio*	(0.0009)	(0.0105)	(0.0128)
tempratio	-0.0168*	0.3907**	0.0202
	(0.0090)	(0.1668)	(0.0905)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
K-P p-value	-	0.1456	-
Hansen J p-value	-	0.6433	-
Outcome Mean	7.4793	7.6963	7.4355
Observations	560811	397813	4572

Notes. Estimates are based on the model in Equation (3.1), using firm-year observations over the period 2011-2019. The dependent variable is value-added (in log) of a firm in a given year. (*tempratio*) indicates the ratio of temporary-to-permanent labor of a firm in a given year. I apply two-stage least square (IV) method in column (2), using Equation (3.2) as first-stage regression. I apply Levinsohn-Petrin (LP) method in column (3), using direct material cost (in log) and electricity cost (in log) as proxies to unobservable productivity shock. The number of firm dummies for including firm-fixed effect in the LP model exceeds the maximum number of variables (120000) in the STATA program. To address this issue, I sample 1,000 firms randomly in each trial and apply the LP method. I iterate 1,000 trials and collect 1,000 sets of coefficients. I go on to calculate the mean and standard errors of each coefficient. I use the property that the expected value of sample mean is equal to population mean. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

3.5.2 Quadratic *tempratio* and the Channel Effect of Temporary Employment

Next, I consider the properties of each channel through which temporary employment affects labor productivity. A firm can expect the most positive effect of flexibility from temporary employment when the firm hires the first unit of temporary workers to address a demand shock that is not covered by the existing permanent labor. The positive effect of flexibility will decrease as the number of temporary workers increases. Likewise, screening will have its most positive effect at the beginning of temporary employment since it signals to temporary workers that they can be converted to permanent workers. This effect will also decrease as the number of temporary workers increases. On the other hand, the spillover effect of temporary employment on permanent workers is initially small and it grows as temporary workers become a majority in a firm. When temporary workers are in the majority, permanent workers may either be discouraged from working hard because temporary workers threaten their job or encouraged (spurred) to work hard to maintain their permanent jobs. The spillover effect can thus be either negative or positive. However, the effect of human capital will be constant because temporary workers are usually less educated and less trained regardless of how many of a firm's employees are temporary. Many studies have shown that temporary employment positively affects labor productivity at the beginning, but becomes negative as temporary workers makes up a large portion of the firm (Beckmann and Kuhn, 2009; Hirsch and Mueller, 2012; Nielen and Schiersch, 2014).

To examine the relationship between temporary employment and labor productivity and verify whether the relationship of the two varies along with *tempratio*, I add squared *tempratio* in Equation (3.1) and interact it with logged inputs in the Cobb-Douglas production function. I estimate a model

(3.3) $Y_{ijt} = X'_{ijt}\beta + (Temporary\ ratio)_{ijt}X'_{ijt}\gamma + (Temporary\ ratio)^2{}_{ijt}X'_{ijt}\rho + \alpha_j + \delta_t + \varepsilon_{ijt}$

where all terms and notations in Equation (3.3) except squared *tempratio* are the same as in Equation (3.1). As before, I adopt the LP method to address unobservable productivity shock, and I use one- and two-year lagged *tempratio* to resolve a problem from a confounder that is correlated with both current *tempratio* and value-added (in log).

First stage regressions are given by

$$(3.4)\quad (Temporary\ ratio)_{ijt} = X'_{ijt}b + Z^{t-1}_{ijt-2}X'_{ijt}c + W^{t-1}_{ijt-2}X'_{ijt}r + \alpha_j + \delta_t + \varepsilon_{ijt}$$

$$(Temporary\ ratio)_{ijt}X_{1,ijt} = X'_{ijt}b_1 + Z^{t-1}_{ijt-2}X'_{ijt}c_1 + W^{t-1}_{ijt-2}X'_{ijt}r_1 + \alpha_{1,j} + \delta_{1,t} + \varepsilon_{1,ijt}$$

$$\vdots$$

$$(Temporary\ ratio)_{ijt}X_{n,ijt} = X'_{ijt}b_n + Z^{t-1}_{ijt-2}X'_{ijt}c_n + W^{t-1}_{ijt-2}X'_{ijt}r_n + \alpha_{n,j} + \delta_{n,t} + \varepsilon_{n,ijt}$$

$$(Temporary\ ratio)^2{}_{ijt}X_{1,ijt}$$

$$= X'_{ijt}b_{n+1} + Z^{t-1}_{ijt-2}X'_{ijt}c_{n+1} + W^{t-1}_{ijt-2}X'_{ijt}r_{n+1} + \alpha_{n+1,j} + \delta_{n+1,t} + \varepsilon_{n+1,ijt}$$

$$\vdots$$

$$(Temporary\ ratio)^2{}_{ijt}X_{n,ijt}$$

$$= X'_{ijt}b_{2n} + Z^{t-1}_{ijt-2}X'_{ijt}c_{2n} + W^{t-1}_{ijt-2}X'_{ijt}r_{2n} + \alpha_{2n,j} + \delta_{2n,t} + \varepsilon_{2n,ijt}$$

where Z^{t-1}_{ijt-2} is a vector of one- and two-year lagged *tempratio*, W^{t-1}_{ijt-2} is a vector of one- and two-year lagged squared *tempratio*, and the remainder of the notation is the same as Equation (3.1), (3.2), and (3.3).

Table 3.3 presents the results from estimating Equation (3.3). As in Table 3.2, the columns represent fixed effect (FE), fixed effect with instruments (FE+IV), and fixed effect with LP (FE+LP), respectively. Column 1 shows that the effect of temporary employment on labor productivity is -0.0083 when there is no temporary employment, and the effect decreases by -

0.0010 as the number of temporary workers increases by the number of permanent workers. However, the result of column 1 in Table 3.3 is inconsistent with that in Table 3.2. Table 3.3 shows that the effect of temporary employment on labor productivity is 0.0037 (positive) for all levels of temporary employment. Column 2 shows that the effect of temporary employment on labor productivity is -0.0726 when there is no temporary employment, and the effect decreases by -0.0024 as the number of temporary workers increases in proportion to the number of permanent workers.

The literature predicts initially positive but decreasing effects of temporary employment on labor productivity through the aggregate channels of flexibility, screening, and negative spillover to permanent workers (solid black in Figure 3.2). If the constant negative effect through the channel of human capital is *small* (blue in Figure 3.2a), then the effect of temporary employment on labor productivity will be positive at the beginning and decrease to negative (red in Figure 3.2a), leading to an inverse U-shaped relationship between labor productivity and temporary employment as shown in Figure 3.2a.

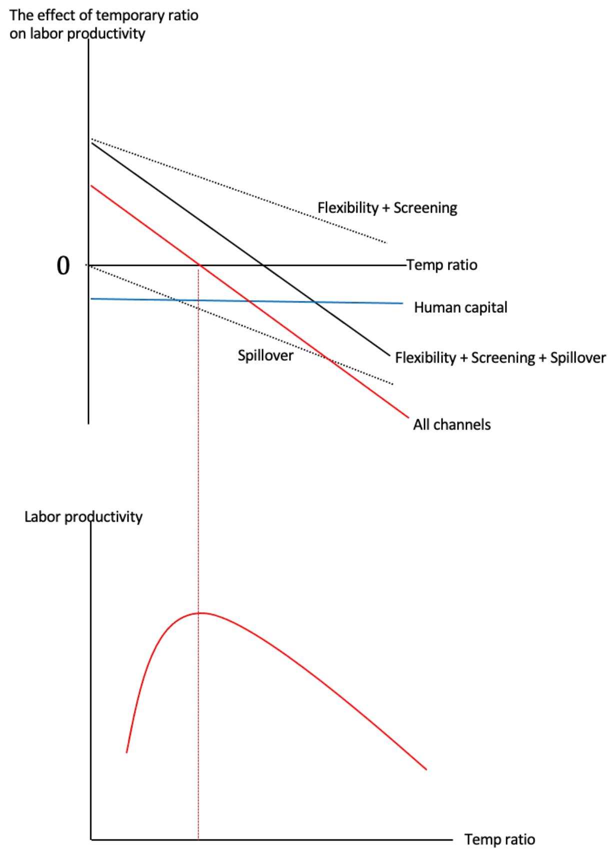
On the other hand, if the constant negative effect through the channel of human capital is *large* (blue in Figure 3.2b), then the effect of temporary employment on labor productivity will be initially negative and grow as temporary employment increases (red in Figure 3.2b). The results show negative relationship between labor productivity and temporary employment for all level of temporary employment. Column 2 shows the same result in the latter case of a *large* negative effect of temporary employment through the channel of human capital because the effect of temporary employment on labor productivity is initially negative (-0.0726) and gets bigger in magnitude along the *tempratio*.

Table 3.3: Effect of *tempratio* on Labor Productivity: Inverse U-Shaped?

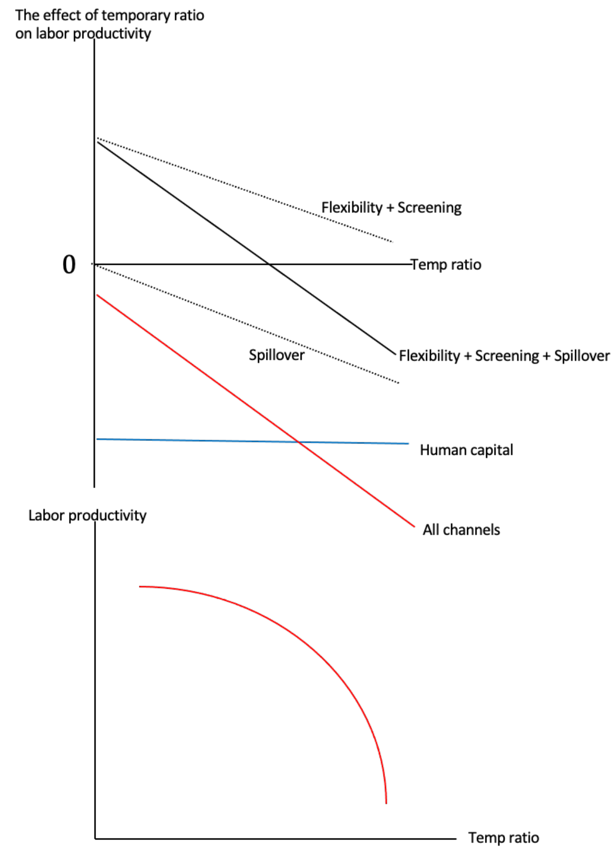
Log (Valueadded)	(1) FE	(2) FE+IV	(3) FE+LP
Log (Labor)	0.6852***	0.6720***	0.4403
	(0.0047)	(0.0116)	(0.0497)
Log (Capital)	0.0814***	0.0696***	0.0894
	(0.0016)	(0.0025)	(0.0210)
Log (Labor)	-0.0083***	-0.0726*	-0.0220
** tempratio*	(0.0025)	(0.0399)	(0.0621)
Log (Labor)	-0.0005***	-0.0012	0.0014
** tempratio* ^{2}	(0.0001)	(0.0017)	(0.0086)
Log (Capital)	-0.0050***	-0.0146	-0.0066
** tempratio*	(0.0009)	(0.0154)	(0.0258)
Log (Capital)	0.0001***	0.0005	0.0008
** tempratio* ^{2}	(0.0000)	(0.0005)	(0.0034)
tempratio	-0.0134*	0.2899	0.0348
	(0.0075)	(0.1986)	(0.1768)
tempratio ^{2}	0.0030***	0.0035	-0.0040
	(0.0004)	(0.0085)	(0.0245)
FirmFE	YES	YES	YES
YearFE	YES	YES	YES
Observations	560811	397813	4572
R-Squared	0.202	0.171	-
K-P p-value	-	0.0000	-
Hansen J p-value	-	0.2726	-
Outcome Mean	7.43545	7.43545	7.43545

Notes. Estimates are based on the model in Equation (3.3), using firm-year observations over the period 2011-2019. The dependent variable is value-added (in log) of a firm in a given year. (*tempratio*) indicates the ratio of temporary-to-permanent labor of a firm in a given year. I apply two-stage least square (IV) method in column (2), using Equation (3.4) as first-stage regression. I apply Levinsohn-Petrin (LP) method in column (3), using direct material cost (in log) and electricity cost (in log) as proxies to unobservable productivity shock. The number of firm dummies for including firm-fixed effect in the LP model exceeds the maximum number of variables in the STATA program. To address this issue, I sample 1,000 firms randomly in each trial and apply the LP method. I iterate 1,000 trials and collect 1,000 sets of coefficients. I go on to calculate the mean and standard errors of each coefficient. I use the property that the expected value of sample mean is equal to population mean. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Figure 3.2: Case of negative spillover (FE+IV) - How big is negative effect of human capital?



(a) negative effect through the channel of human capital is *small*

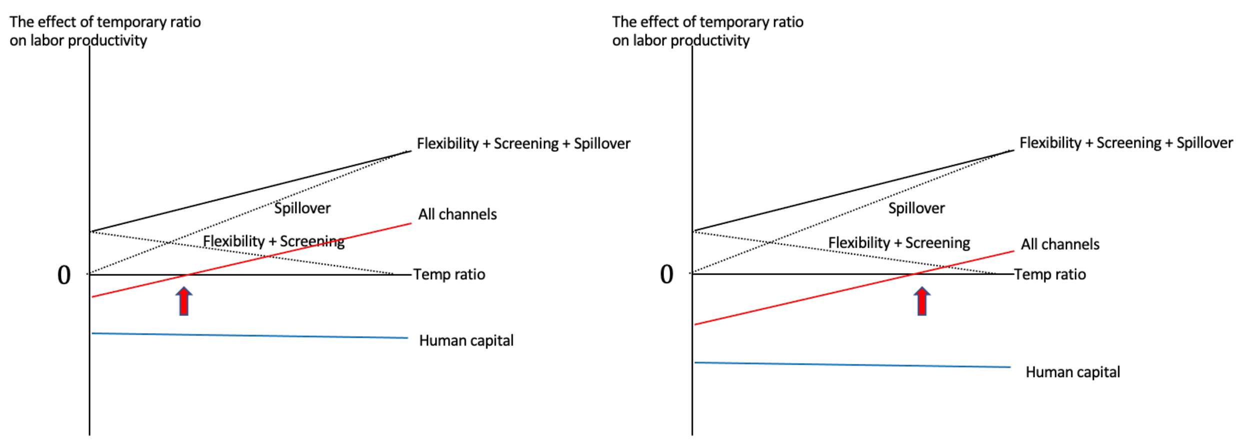


(b) negative effect through the channel of human capital is *large*

What if temporary employment positively affects permanent labor through spillover? If the positive effect through flexibility and screening is small relative to the positive spillover effect, the aggregate effect through flexibility, screening, and spillover will increase in the *tempratio* (solid black in Figure 3.3). When the constant negative effect from the channel of human capital (blue in Figure 3.3) is added to the aggregate positive effect, the total effect (red in Figure 3.3) is likely to be initially negative and become positive. The level of the break-even *tempratio* depends on the level of the negative effect through human capital as shown in Figure 3.3 below: the more the negative effect of human capital, the higher the break-even *tempratio*.

The result in column 3 exactly matches the case above. The effect of temporary employment on labor productivity is -0.0220 when there is no temporary employment and increases by 0.0028 as the number of temporary workers increases in proportion to permanent workers. The break-even *tempratio* is 7.856. Considering the mean value (0.2146) and the standard deviation (1.3894) of the *tempratio*, the break-even *tempratio* of 7.856 is large enough to conclude that the negative effect of temporary employment through human capital outweighs the positive effects from other channels. To sum up, the result of estimating Equation (3.1) and (3.3) indicates that temporary workers' effect on labor productivity through the channel of human capital is *large* enough to outweigh the other channel effects (flexibility, screening, and spillover).

Figure 3.3: Case of Positive spillover (FE+LP) - How big is negative effect of human capital?



(a) negative effect through the channel of human capital is *small* (b) negative effect through the channel of human capital is *large*

3.5.3 Complementarity in Permanent Employment and Technology Shift

These results verify that temporary employment decreases labor productivity after the implementation of temporary EPL (2011-2019) in South Korea. The negative effect of temporary employment on labor productivity is mainly due to the low level of human capital in temporary employment. It is equivalent to that permanent employment increase a firm's labor productivity. To explain the continuously increasing trend of permanent ratio, it is useful to consider the concept of complementarity in permanent employment. If there exists a complementarity in permanent employment, i.e., the effect of a firm's permanent employment is increasing in permanent employment in the upstream industries, a Big Push can make a continuous increase of permanent ratio. It is possible to think that temporary EPL serves as a Big Push in the permanent employment. Before the implementation of temporary EPL, firms may not increase its permanent ratio since others do not. However, the implementation of temporary EPL damages the merits of flexibility and screening. It makes a firm expect that other firms will hire permanent workers rather than temporary workers. To explain whether there exists complementarity in permanent employment, I use the model

(3.5) $Y_{ijt} = \beta_0 + \beta_P(Permanent\ ratio)_{ijt} + \beta_F(Forward)_{it}$

$$+\beta_{PF}(Permanent\ ratio)_{ijt}(Forward)_{it} + \mathrm{W}_{it}^{\prime}\Gamma + \alpha_j + \delta_t + \varepsilon_{ijt}$$

where Y_{ijt} is a firm's profit or price and $Permanent\ ratio_{ijt}$ is the ratio of permanent to the total employment (hereafter *permratio*) in firm *j* in industry *i* in time *t*. A variable of $Forward_{it}$ is the weighted sum of *permratio* (hereafter *forward*) in *i*'s upstream industries *k* in time *t* with input coefficients in 2005 IO table as weights.[69] The vector W_{it} indicates a set of industry

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[69] $Forward_{it} = \sum_k \alpha_{ki}(Permanent\ ratio)_{kt}$

characteristics of average productivity ($\frac{Production}{Captial}$, $\frac{Production}{Labor}$, $\frac{Value-added}{Production}$), profitability ($\frac{Profit}{Production}$, $\frac{Profit}{Sales}$), and trade[70] ($\sum_{t=2011}^{2019}\left(\frac{exports}{total\ supply}\right)_{i2005} Year_t$, $\sum_{t=2011}^{2019}\left(\frac{imports}{total\ supply}\right)_{i2005} Year_t$). I also adopt firm- ($\alpha_j$) and time-fixed effects (δ_t). An error term ε_{ijt} represents unobserved characteristics that affect a firm's profit. Standard errors are clustered at a firm level and robust to heteroskedasticity. The parameter of interest in Equation (3.5) is β_{PF}, which is the coefficient on the interaction variable, $permratio * forward$. If it is positive, complementarity exists in permanent employment.

$Forward_{it}$ and the control variables W_{it}, are industry level variables, and thus it is likely that they are exogenous. A firm's *permratio*, however, could be endogenous because (i) a firm's unobserved characteristics in the error term, ε_{ijt}, could affect both *permratio* and $Outcome_{ijt}$, and (ii) outcome variable of a firm's profit could reversely affect *permratio*. To address the problem of endogeneity in *permratio*, I adopt one- and two-year lagged *permratios* as instrumental variables provided that it is less likely for the shocks to be effective more than one year and affects both lagged *permratios* and the current outcome variables. So, the instrumental variables are *exogenous* to the unobserved shocks in the current error term. Moreover, instruments of one- and two-year lagged *permratios* are likely to be *relevant* to an endogenous regressor of current *permratio* because both are the same property of a firm except the time. First stage regressions are given by

[70] Exports, imports, and total supply (=total output + imports) come from 1980 I/O table. The ratio of exports-to-total supply and imports-to-total supply are interacted with year dummies.

$$(3.6)\quad (Permanent\ ratio)_{ijt} = b_0 + Z_{ijt-2}^{t-1} b_s + Z_{ijt-2}^{t-1} (Forward)_{it} b_{sf}$$

$$+ b_f (Forward)_{it} + \mathrm{W}_{it}^{'} \mathrm{c} + a_j + d_t + e_{ijt}$$

$$(Permanent\ ratio)_{ijt} (Forward)_{it} = b_{1,0} + Z_{ijt-2}^{t-1} b_{1,s} + Z_{ijt-2}^{t-1} (Forward)_{it} b_{1,sf}$$

$$+ b_{1,f} (Forward)_{it} + \mathrm{W}_{it}^{'} \mathrm{c}_1 + a_{1,j} + d_{1,t} + e_{1,ijt}$$

where Z_{ijt-2}^{t-1} is a vector of one- and two-year lagged *permratios*. The remainder of the notation is the same as in Equation (3.5).

Table 3.4: Complementarity: profit, permanent-to-total labor ratio

Profit	(1) FE	(2) FE+IV	(3) FE	(4) FE+IV	(5) FE	(6) FE+IV	(7) FE	(8) FE+IV
permratio	-514	-11891	-129	-14512	-130	-14543	-114	-12810
	(1152)	(17616)	(1235)	(19972)	(1236)	(19880)	(1209)	(18901)
forward	-945	-35049	-52557	-100020	-52343	-100001	-57120	-107321
	(31282)	(51079)	(45262)	(70627)	(44554)	(69794)	(48915)	(71469)
permratio **forward*	1558	35415	432	29488	434	29468	389	29032
	(1490)	(34654)	(1522)	(35759)	(1522)	(35730)	(1682)	(34548)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry-level Controls								
Productivity	N	N	Y	Y	Y	Y	Y	Y
Profitability	N	N	N	N	Y	Y	Y	Y
Trade	N	N	N	N	N	N	Y	Y
Observations	535256	381592	535255	381591	535244	381582	506617	361642
Outcome Mean	7659	9523	7659	9523	7659	9524	7976	9919
K-P p-value	-	0.0000	-	0.0000	-	0.0000	-	0.0000
Hansen J p-value	-	0.8818	-	0.9997	-	0.9997	-	0.9919
Break-even Forward ratio	0.3299	0.3358	0.2986	0.4921	0.2995	0.4935	0.2931	0.4412

Notes. Estimates are based on the model in Equation (3.5), using firm-year observations over the year 2011-2019. The dependent variable is profit of a firm in a given year. *permratio* indicates the ratio of permanent-to-total labor and *forward* indicates the weighted sum of *permratio* in the upstream industries with input coefficients as weights. I apply two-stage least square (IV) method in column (2), (4), (6), and (8) using Equation (3.6) as first-stage regression. Controls for productivity include firm- and industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include firm- and industry-level ratios of profit-to-production, and profit-to-sales. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3.5: Complementarity: price, permanent-to-total labor ratio

Price	(1) FE	(2) FE+IV	(3) FE	(4) FE+IV	(5) FE	(6) FE+IV	(7) FE	(8) FE+IV
permratio	3.8246***	58.1061***	3.9530***	60.6820***	4.0259***	61.1638***	2.8263***	44.2319***
	(0.3653)	(9.2424)	(0.3618)	(9.5008)	(0.3593)	(9.5525)	(0.3425)	(7.4092)
forward	59.2227***	122.1049***	74.2660***	139.6313***	77.2868***	143.3783***	63.6785***	112.2532***
	(2.5621)	(12.4844)	(2.6438)	(12.7863)	(2.6393)	(12.8547)	(2.6520)	(10.1719)
permratio	-5.3115***	-84.3116***	-5.4002***	-86.8816***	-5.5017***	-87.7538***	-3.6684***	-62.3808***
* *forward*	(0.5503)	(13.4445)	(0.5420)	(13.7719)	(0.5380)	(13.8454)	(0.5108)	(10.7997)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry-level Controls								
Productivity	N	N	Y	Y	Y	Y	Y	Y
Profitability	N	N	N	N	Y	Y	Y	Y
Trade	N	N	N	N	N	N	Y	Y
Observations	605043	424106	605041	424104	604564	423719	563327	394989
Outcome Mean	100.7568	100.7364	100.7568	100.7364	100.7544	100.7338	100.7463	100.7868
K-P p-value	-	0.0000	-	0.0000	-	0.0000	-	0.0000
Hansen J p-value	-	0.0000	-	0.0000	-	0.0000	-	0.0000
Break-even Forward ratio	0.7201	0.6892	0.7320	0.6984	0.7318	0.6970	0.7704	0.7091

Notes. Estimates are based on the model in Equation (5), using firm-year observations over the year 2011-2019. The dependent variable is price of a firm in a given year. *permratio* indicates the ratio of permanent-to-total labor and *forward* indicates the weighted sum of *permratio* in the upstream industries with input coefficients as weights. I apply two-stage least square (IV) method in column (2), (4), (6), and (8) using Equation (6) as first-stage regression. Controls for productivity include firm- and industry-level ratios of production-to-capital, production-to-labor, and value-added-to-production, and controls for profitability include firm- and industry-level ratios of profit-to-production, and profit-to-sales. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3.4 and 3.5 show the result from estimating variants of Equation (3.5) when Y_{ijt} is profit and price, respectively. Each column in Table 3.4 shows that a coefficient on the interaction variable is positive regardless of additional control variables. In contrast, each column in Table 3.5 shows that a coefficient on the interaction variable is negative. The results imply that the more firms hire permanent workers, the better it is for a firm to hire permanent workers. In other words, there is a complementarity in permanent employment. Considering that temporary EPL serves as a Big Push to let firms expect other firms will hire permanent rather than temporary workers, and that complementarity exists in permanent employment, the trend of increasing permanent employment can be explained. Furthermore, that complementarity in permanent employment holds implies that permanent workers in the upstream industries promote a firm's technology shift toward permanent labor-intensive techniques.

It is remarkable to see that the effect of permanent workers in the upstream industries is negative on a firm's profit and it is positive on a firm's price when *permratio* is zero. Both are adverse effects to the firm, and so it is predicted that the firm accessing increased permanent workers outside the firm will hire permanent workers to change its production technology from intermediate input-intensive (and also capital-intensive) toward permanent labor-intensive to get less impact from an expensive intermediate input. Hence, the adverse effects of permanent workers in the upstream industries, $forward$, are shrinking (in magnitude) in a firm's *permratio.*

To examine whether permanent employment in the upstream industries cause a marginal firm's technological shift from capital-intensive to permanent labor-intensive production technique, I construct a model by taking a log on Cobb-Douglas production function and interacting logged inputs with a variable of permanent employment outside a firm, $forward$. I estimate the model[71]

$$(3.7)\quad Y_{ijt} = X'_{ijt}\beta + (Forward)_{it}X'_{ijt}\gamma + \alpha_j + \delta_t + \varepsilon_{ijt}$$

where Y_{ijt} is either a log of production or a log of value-added and X_{ijt} is a vector of logged inputs (permanent labor, temporary labor, capital, and intermediate input) in firm j in industry i in time t. A variable of $Forward_{it}$ (*forward*) is the weighted sum of permanent-to-total worker ratios in i's upstream industries k in time t with input coefficients in 2005 I-O table as weights. The variables α_j and δ_t represent firm- and year-fixed effect respectively to get rid of firm-specific characteristics over time and year-specific properties across entities. The error term ε_{ijt} refers to unobservable characteristics. Standard errors are clustered at a firm level.

In Equation (3.7), there could be an endogeneity incurred from an unobserved productivity shock in the error term. The shock could affect both (logged) inputs and value-added, and hence, the estimators could be biased. I adopt the Levinsohn-Petrin[72] (LP) method to address this endogeneity problem in the identification of the Cobb-Douglas production function. Refer to Appendix C.1 about applying LP method in Equation (3.7).

Table 3.6 shows the results from estimating variants of Equation (3.7). As predicted, most columns show that the output elasticity of intermediate input and capital are decreasing while the output elasticity of permanent labor is increasing in permanent employment in the upstream industries. The results show that temporary EPL that was supposed to protect

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[71] Akerman et al. (2015) use the same approach to examine the effect of broadband adoption on the productivity of each production input.

[72] Levinsohn-Petrin (2003) use intermediate inputs as proxies for unobserved productivity shock. Their method resolves the problem of zero-investment in nontrivial number of firms in Olley-Pakes (1996) that use investment as a proxy.

temporary workers seems to burden firms (adverse effects on profit and price) as well as economic growth (reduced output elasticity of capital).

Table 3.6: Permanent Employment and Technology Shift

	D.V.= *Log (Production)*		D.V.= *Log (Value-added)*
	(1)	(2)	(3)
	FE	FE	FE
Log (Intermediate)	0.5565***	0.5261***	
	(0.0180)	(0.0315)	
Log (Permanent)	0.1418***	0.1431***	0.2771***
	(0.0143)	(0.0198)	(0.0283)
Log (Temporary)		0.0478***	0.0926***
		(0.0066)	(0.0111)
Log (Capital)		0.0428***	0.1149***
		(0.0105)	(0.0159)
Log (Intermediate)	-0.1684***	-0.1217**	
** forward*	(0.0256)	(0.0472)	
Log (Permanent)	0.2274***	0.1621***	0.2607***
** forward*	(0.0213)	(0.0313)	(0.0419)
Log (Temporary)		0.0037	-0.0070
** forward*		(0.0099)	(0.0162)
Log (Capital)		0.0007	-0.0434*
** forward*		(0.0159)	(0.0229)
forward	0.2036	0.0040	-1.5176***
	(0.2052)	(0.3963)	(0.3543)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Outcome Mean	8.3185	8.2470	7.3981
Observations	593564	149727	149223

Notes. Estimates are based on the model in Equation (3.7), using firm-year observations over the period 2011-2019. The dependent variable is production (in log) of a firm in a given year in column (1) and (2) while value-added (in log) of a firm in a given year in column (3). (*forward*) indicates the weighted sum of *permratio* in the upstream industries with input coefficients as weights. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

3.6 Conclusion

There has been a divergence in employment between permanent and temporary workers. After the implementation of temporary EPL in 2007, the number of permanent workers is increasing each year while that of temporary workers is slowly declining. The proportion of permanent workers in all wage workers that had been maintained between 50 and 60 percent in 1990s and 2000s kept increasing in 2010s, reaching 70 percent in 2020. In this paper I focus on explaining the divergence in employment. First, I find the effect of temporary employment through channels of flexibility and screening are overwhelmed by the channel of human capital in 2011-2019. This justifies that the temporary EPL plays a role as a Big Push so that firms expect others to increase their employment with permanent workers rather than temporary since temporary employment loses its merit of flexibility and screening. Second, I find that there exists complementarity in permanent employment. The divergence in employment between permanent and temporary workers in the 2010s, hence, can be explained by the combination of complementarity in permanent employment and Big Push of temporary EPL. Third, permanent employment in upstream industries promote a firm’s technology shift from capital-intensive toward permanent labor-intensive production techniques. This change would amplify diminishing returns on capital and prevent the country from achieving sustained economic growth.

Appendix A

Human Capital, Technology and Sustained Growth in South Korea

A.1 Input-Output Table

Figure A.1: Input-Output Table

		endogenous sector								exogenous sector				import	total output
		1	…	i	…	j	…	n	intermediate demand total	consumption	investment	export	final demand total		
endogenous sector	1	X_{11}	…	X_{1i}	…	X_{1j}	…	X_{1n}	W_1	C_1	I_1	E_1	Y_1	M_1	X_1
	⋮								⋮						
	i	X_{i1}	…	X_{ii}	…	X_{ij}	…	X_{in}	W_i	C_i	I_i	E_i	Y_i	M_i	X_i
	⋮								⋮						
	j	X_{j1}	…	X_{ji}	…	X_{jj}	…	X_{jn}	W_j	C_j	I_j	E_j	Y_j	M_j	X_j
	⋮								⋮						
	n	X_{n1}	…	X_{ni}	…	X_{nj}	…	X_{nn}	W_n	C_n	I_n	E_n	Y_n	M_n	X_n
	intermediate input total	U_1	…	U_i	…	U_j	…	U_n							
exogenous sector	compensation of employees	R_1	…	R_i	…	R_j	…	R_n							
	operating surplus	S_1	…	S_i	…	S_j	…	S_n							
	consumption of fixed capital	D_1	…	D_i	…	D_j	…	D_n							
	net taxed in products	T_1	…	T_i	…	T_j	…	T_n							
	value added total	V_1	…	V_i	…	V_j	…	V_n							
total input		X_1	…	X_1	…	X_j	…	X_n							

A.2 Solow Model

$$Y = AF(K, L)$$

$$\frac{Y}{L} = AF\left(\frac{K}{L}\right) \Leftrightarrow y = Af(k)$$

$$\dot{K} = I - \delta K = sY - \delta K = sAF(K, L) - \delta K$$

$$\frac{\dot{K}}{L} = sAf(k) - \delta k$$

$$k = \frac{K}{L} \Leftrightarrow K = kL$$

$$\dot{K} = \dot{k}L + k\dot{L}$$

$$\frac{\dot{K}}{L} = \dot{k} + k\frac{\dot{L}}{L} = \dot{k} + nk = sAf(k) - \delta k$$

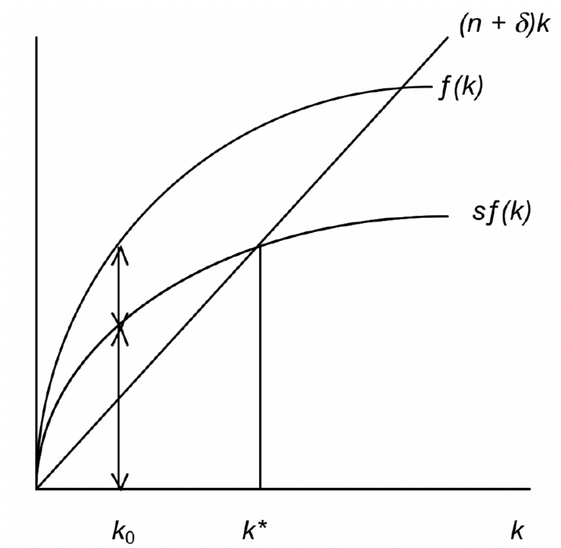
$$\dot{k} = sAf(k) - (n + \delta)k$$

$$Suppose\ Y = AF(K, L) = AK^{\alpha}L^{1-\alpha}$$

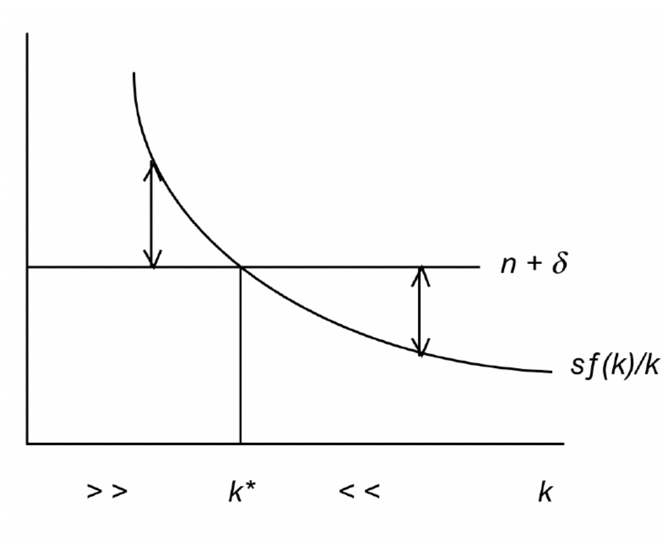
$$\frac{Y}{L} = A\left(\frac{K}{L}\right)^{\alpha} \Leftrightarrow y = Ak^{\alpha}$$

$$\dot{k} = sAk^{\alpha} - (n + \delta)k$$

Delaying diminishing return by increasing capital elasticity (α)
Human capital accumulation in the upstream industries serves as a Big Push to overcome coordination failure and promote a firm's technology shift toward capital-intensive production techniques.



(n + δ)k
f(k)
sf(k)
k0
k*
k



n + δ
sf(k)/k
> >
k*
< <
k

A.3 Theoretical Framework

$$X = \left[\int y_j^{\frac{\eta-1}{\eta}} dj\right]^{\frac{\eta}{\eta-1}}$$

$$TRS^{73} = \frac{\frac{\partial X}{\partial y_j}}{\frac{\partial X}{\partial y_{j'}}} = \left(\frac{y_{j'}}{y_j}\right)^{\frac{1}{\eta}} = \frac{p_j}{p_{j'}} \;\; \forall j'$$

$$y_{j'} = \left(\frac{p_j}{p_{j'}}\right)^{\eta} \cdot y_j = \left(\frac{p_{j'}}{p_j}\right)^{-\eta} \cdot y_j \;\; \forall j'$$

$$X = \left[y_j^{\frac{\eta-1}{\eta}} + \left\{\left(\frac{p_{j'}}{p_j}\right)^{-\eta} \cdot y_j\right\}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \;\; \forall j' \; = \left[y_j^{\frac{\eta-1}{\eta}} + \left(\frac{p_{j'}}{p_j}\right)^{1-\eta} \cdot y_j^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \;\; \forall j'$$

$$= \left(\frac{p_j^{1-\eta} + p_{j'}^{1-\eta}}{p_j^{1-\eta}}\right)^{\frac{\eta}{\eta-1}} \cdot y_j \;\; \forall j'$$

$$y_j = \left(\frac{p_j^{1-\eta} + p_{j'}^{1-\eta}}{p_j^{1-\eta}}\right)^{\frac{\eta}{1-\eta}} \cdot X \;\; \forall j' \;\; = \left[\frac{\left[\int p_j^{1-\eta} dj\right]^{\frac{1}{1-\eta}}}{p_j}\right]^{\eta} \cdot X = \left[\frac{P}{p_j}\right]^{\eta} \cdot X$$

$$where \; P = \left[\int p_j^{1-\eta} dj\right]^{\frac{1}{1-\eta}}$$

[73] TRS = Technical Rate of Substitution

A.4 Summary Statistics: Input elasticity

(A.1) $Y_{ijt} = \sum_{t=1982}^{1996} Year_t \, X'_{ijt}\beta_t + \alpha_j + \varepsilon_{ijt}$

where Y_{ijt} is a log of value-added and X_{ijt} is a vector of logged inputs (unskilled labor, skilled labor, and capital) in firm *j* in industry *i* in time *t*. A variable of $Year_t$ is the year dummy variable. The variable α_j represents firm-fixed effect to get rid of firm-specific characteristics over time. The error term ε_{ijt} refers to unobservable characteristics. Standard errors are clustered at a firm level.

Table A.1: Input Elasticity

Log (Value-added)	Input = Unskilled labor			Input = Skilled labor			Input = Capital		
	Coefficient (Standard Error)	95% Confidence Interval (Lower)	(Upper)	Coefficient (Standard Error)	95% Confidence Interval (Lower)	(Upper)	Coefficient (Standard Error)	95% Confidence Interval (Lower)	(Upper)
Log(Input)									
* *Year1982*	0.5213591***	0.5093312	0.5333870	0.2565411***	0.2452047	0.2678775	0.115071***	0.1075483	0.1225937
	(0.0061367)			(0.0057839)			(0.0038381)		
* *Year1983*	0.5170523***	0.5058172	0.5282874	0.2324252***	0.2216677	0.2431827	0.1159154***	0.1084907	0.1233401
	(0.0057322)			(0.0054885)			(0.0037881)		
* *Year1984*	0.5573958***	0.5469449	0.5678467	0.2431786***	0.2332947	0.2530625	0.1063924***	0.0997651	0.1130197
	(0.0053321)			(0.0050428)			(0.0033813)		
* *Year1985*	0.5540288***	0.5442078	0.5638498	0.2473093***	0.2382129	0.2564057	0.1042869***	0.0979796	0.1105942
	(0.0050107)			(0.004641)			(0.003218)		
* *Year1986*	0.5614165***	0.5518141	0.5710189	0.2416847***	0.2328053	0.2505641	0.1104117***	0.1043776	0.1164458
	(0.0048992)			(0.0045303)			(0.0030786)		
* *Year1987*	0.5655456***	0.5564630	0.5746282	0.2390715***	0.2308469	0.2472961	0.109337***	0.1036018	0.1150722
	(0.004634)			(0.0041962)			(0.0029261)		
* *Year1988*	0.5461895***	0.5373719	0.5550071	0.2435843***	0.2359207	0.2512479	0.1017284***	0.0962802	0.1071766
	(0.0044988)			(0.00391)			(0.0027797)		
* *Year1989*	0.5565134***	0.5475362	0.5654906	0.2522074***	0.2445767	0.2598381	0.1035901***	0.0983308	0.1088494
	(0.0045802)			(0.0038932)			(0.0026833)		
* *Year1990*	0.5368185***	0.5280744	0.5455626	0.2543175***	0.2470355	0.2615995	0.1169979***	0.1116244	0.1223714
	(0.0044613)			(0.0037153)			(0.0027416)		
* *Year1991*	0.5131475***	0.5047636	0.5215314	0.2686006***	0.2616036	0.2755976	0.1149252***	0.1096301	0.1202203
	(0.0042775)			(0.0035699)			(0.0027016)		
* *Year1992*	0.5120186***	0.5037258	0.5203114	0.2680436***	0.2610227	0.2750645	0.1230257***	0.1175708	0.1284806
	(0.004231)			(0.0035821)			(0.0027831)		
* *Year1993*	0.5121574***	0.5035101	0.5208047	0.2668551***	0.2596162	0.2740940	0.1138543***	0.1086042	0.1191044
	(0.0044119)			(0.0036933)			(0.0026786)		
* *Year1994*	0.5053059***	0.4967421	0.5138697	0.2701715***	0.2630818	0.2772612	0.1211969***	0.1160278	0.1263660
	(0.0043693)			(0.0036172)			(0.0026373)		
* *Year1995*	0.5011774***	0.4923631	0.5099917	0.2673107***	0.2600867	0.2745347	0.1290409***	0.1236397	0.1344421
	(0.0044971)			(0.0036857)			(0.0027557)		
* *Year1996*	0.5005794***	0.4911434	0.5100154	0.2768489***	0.2689891	0.2847087	0.12543***	0.1195849	0.1312751
	(0.0048143)			(0.0040101)			(0.0029822)		

Notes. Estimates are based on the model in Equation (A.3), using firm-year observations over the period 1982-1996. The dependent variable is value-added (in log) of a firm in a given year. (Input) refers to unskilled labor, skilled labor, and capital. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

A.5 Summary Statistics: "within firm" average input each year

(A.2) $Y_{ijt} = \sum_{t=1982}^{1996} Year_t \, \beta_t + \alpha_j + \varepsilon_{ijt}$

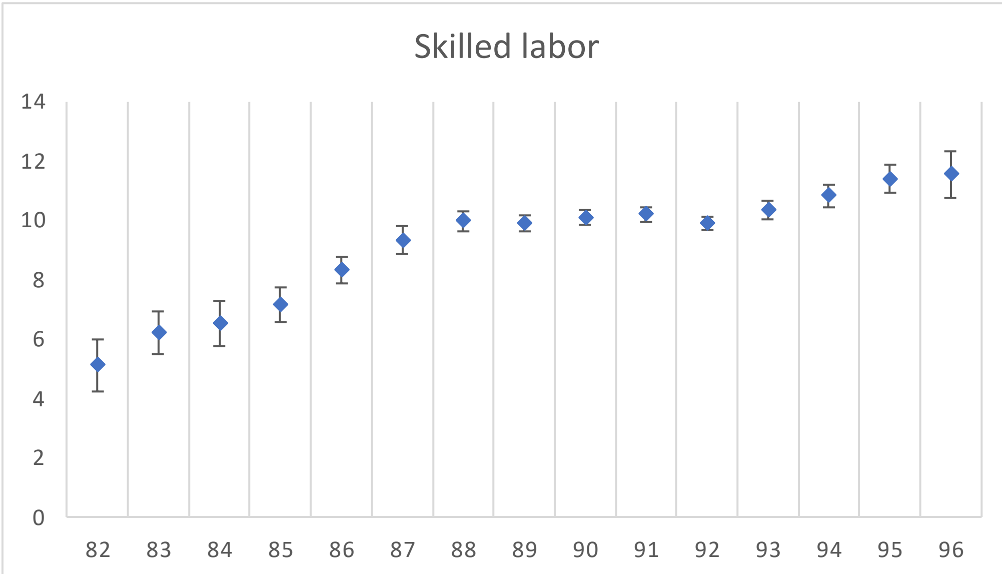
where Y_{ijt} is either skilled or unskilled labor in firm *j* in industry *i* in time *t*. A variable of $Year_t$ is the year dummy variable. The variable α_j represents firm-fixed effect to get rid of firm-specific characteristics over time. The error term ε_{ijt} refers to unobservable characteristics. Standard errors are clustered at a firm level.

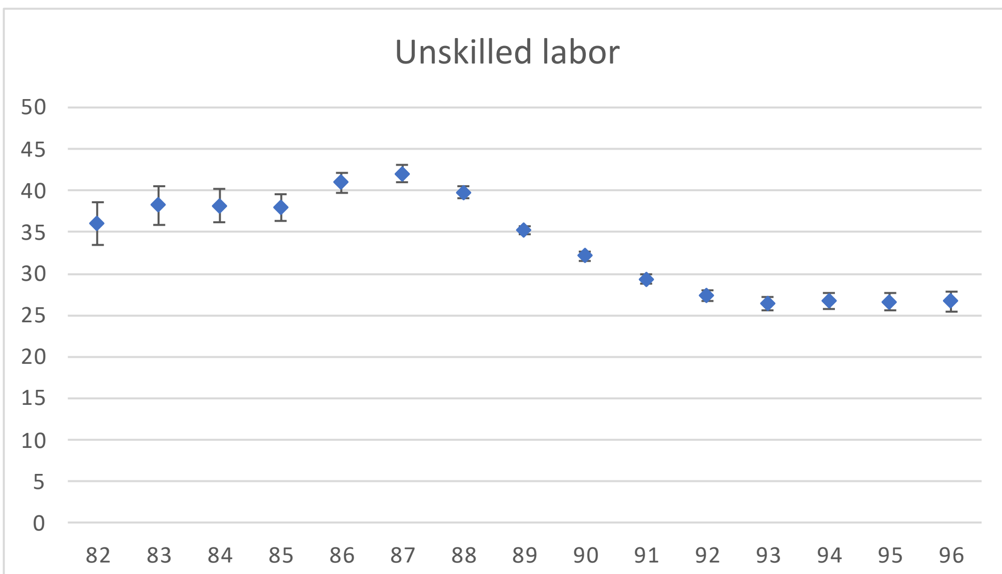
Table A.2: Within Firm Average Input

	D.V. = Skilled labor			D.V. = Unskilled labor		
	Coefficient (Standard Error)	95% Confidence Interval (Lower)	(Upper)	Coefficient (Standard Error)	95% Confidence Interval (Lower)	(Upper)
Year1982	5.118014***	4.240682	5.995346	35.99648***	33.44743	38.54553
	(0.4476185)			(1.300534)		
Year1983	6.233945***	5.509743	6.958147	38.20574***	35.84897	40.56251
	(0.3694907)			(1.202433)		
Year1984	6.535269***	5.784927	7.285611	38.1834***	36.17417	40.19263
	(0.3828275)			(1.025116)		
Year1985	7.171212***	6.595679	7.746745	38.0034***	36.36578	39.64102
	(0.2936395)			(0.8355216)		
Year1986	8.334821***	7.866784	8.802858	40.97889***	39.7698	42.18798
	(0.2387946)			(0.616883)		
Year1987	9.325562***	8.850406	9.800718	42.0516***	41.04451	43.05869
	(0.2424264)			(0.5138209)		
Year1988	9.972508***	9.627565	10.317451	39.78678***	39.04676	40.5268
	(0.1759912)			(0.37756)		
Year1989	9.891645***	9.619279	10.164012	35.25045***	34.74661	35.75429
	(0.1389625)			(0.2570633)		
Year1990	10.10108***	9.843407	10.358762	32.15801***	31.58262	32.7334
	(0.1314681)			(0.2935679)		
Year1991	10.21497***	9.971667	10.458273	29.35993***	28.77393	29.94593
	(0.1241342)			(0.2989793)		
Year1992	9.896415***	9.682248	10.110582	27.37055***	26.73854	28.00256
	(0.1092687)			(0.3224547)		
Year1993	10.36121***	10.0524	10.670022	26.3901***	25.58222	27.19798
	(0.1575572)			(0.4121821)		
Year1994	10.84082***	10.45261	11.229027	26.7283***	25.80583	27.65077
	(0.1980646)			(0.4706461)		
Year1995	11.3896***	10.91779	11.861405	26.59602***	25.55738	27.63466
	(0.240717)			(0.5299182)		
Year1996	11.54893***	10.78075	12.317105	26.64668***	25.44607	27.84729
	(0.3919262)			(0.6125586)		

Notes. Estimates are based on the model in Equation (A.3), using firm-year observations over the period 1982-1996. The dependent variable is either skilled labor or unskilled labor of a firm in a given year. (Year19**) refers to year dummy variable. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%

Figure A.2: Within Firm Average level of Inputs each year





A.6 Robustness Check: Levinsohn-Petrin method

Table A.3: Technology Shift, $Skill\ ratio_{it}$, Levinsohn-Petrin method

D.V.= *Log (Value-added)*	(1) FE	(2) LP	(3) LP	(4) LP
Log (Unskilled)	0.5682***	0.1753***	0.3287***	0.3953***
	(0.0042)	(0.0044)	(0.0024)	(0.0612)
Log (Skilled)	0.2370***	0.1235***	0.1470***	0.1471***
	(0.0034)	(0.0049)	(0.0028)	(0.0449)
Log (Capital)	0.1098***	0.1263***	0.0606***	0.1028***
	(0.0022)	(0.0030)	(0.0016)	(0.0399)
Log (Unskilled)	-0.1112***	-0.0180	-0.1446***	-0.1297
$*\ Skill\ ratio_{it}$	(0.0100)	(0.0121)	(0.0050)	(0.1414)
Log (Skilled)	0.0569***	-0.0035	0.0801***	0.0560
$*\ Skill\ ratio_{it}$	(0.0085)	(0.0125)	(0.0039)	(0.1100)
Log (Capital)	0.0110**	0.0237***	0.0797***	0.0229
$*\ Skill\ ratio_{it}$	(0.0054)	(0.0030)	(0.0034)	(0.0904)
$Skill\ ratio_{it}$	0.2332***	0.3955***	0.0402*	0.1868
	(0.0318)	(0.0294)	(0.0210)	(0.5202)
FirmFE	Y	N	N	Y
YearFE	Y	N	Y	Y
Observations	710656	617109	617109	4027
Outcome Mean	6.0292	6.0292	6.0292	5.6529

Notes. Estimates are based on the model in Equation (1.3), using firm-year observations over the period 1982-1996. The dependent variable is value-added (in log) of a firm in a given year in all columns. ($Skill\ ratio_{it}$) indicates the ratio of skilled-to-unskilled labor in the industry to which a firm belongs. I apply Levinsohn-Petrin (LP) method in column (2), (3), and (4), using direct material cost (in log) and electricity cost (in log) as proxies to unobservable productivity shock. Column (3) and (4) include year dummies, and column (4) include firm dummies. The number of firm dummies, however, exceeds the maximum number of variables in the STATA program. To address this issue, I sample 1,000 firms randomly in each trial and apply the LP method. I iterate 1,000 trials and collect 1,000 sets of coefficients. I go on to calculate the mean and standard errors of each coefficient. I use the property that the expected value of sample mean is equal to population mean. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.4: Technology Shift, $Forward_{it}$, Levinsohn-Petrin method

D.V.= *Log (Value-added)*	(1) FE	(2) LP	(3) LP	(4) LP
Log (Unskilled)	0.5510***	0.2167***	0.3575***	0.3814***
	(0.0069)	(0.0073)	(0.0037)	(0.0965)
Log (Skilled)	0.2258***	0.0802***	0.1303***	0.1571**
	(0.0055)	(0.0065)	(0.0055)	(0.0770)
Log (Capital)	0.1012***	0.1354***	0.0573***	0.1001*
	(0.0037)	(0.0040)	(0.0031)	(0.0587)
Log (Unskilled)	-0.0967***	-0.2652***	-0.4123***	-0.1380
** Forward*	(0.0276)	(0.0261)	(0.0134)	(0.3717)
Log (Skilled)	0.1408***	0.2440***	0.2458***	0.0466
** Forward*	(0.0224)	(0.0248)	(0.0203)	(0.3125)
Log (Capital)	0.0550***	-0.0124	0.1345***	0.0455
** Forward*	(0.0150)	(0.0114)	(0.0138)	(0.2213)
Forward	-0.0248	1.8234***	0.5034***	0.1225
	(0.0955)	(0.0479)	(0.0711)	(1.3673)
FirmFE	Y	N	N	Y
YearFE	Y	N	Y	Y
Observations	710656	617109	617109	4027
Outcome Mean	6.0292	6.0292	6.0292	5.6529

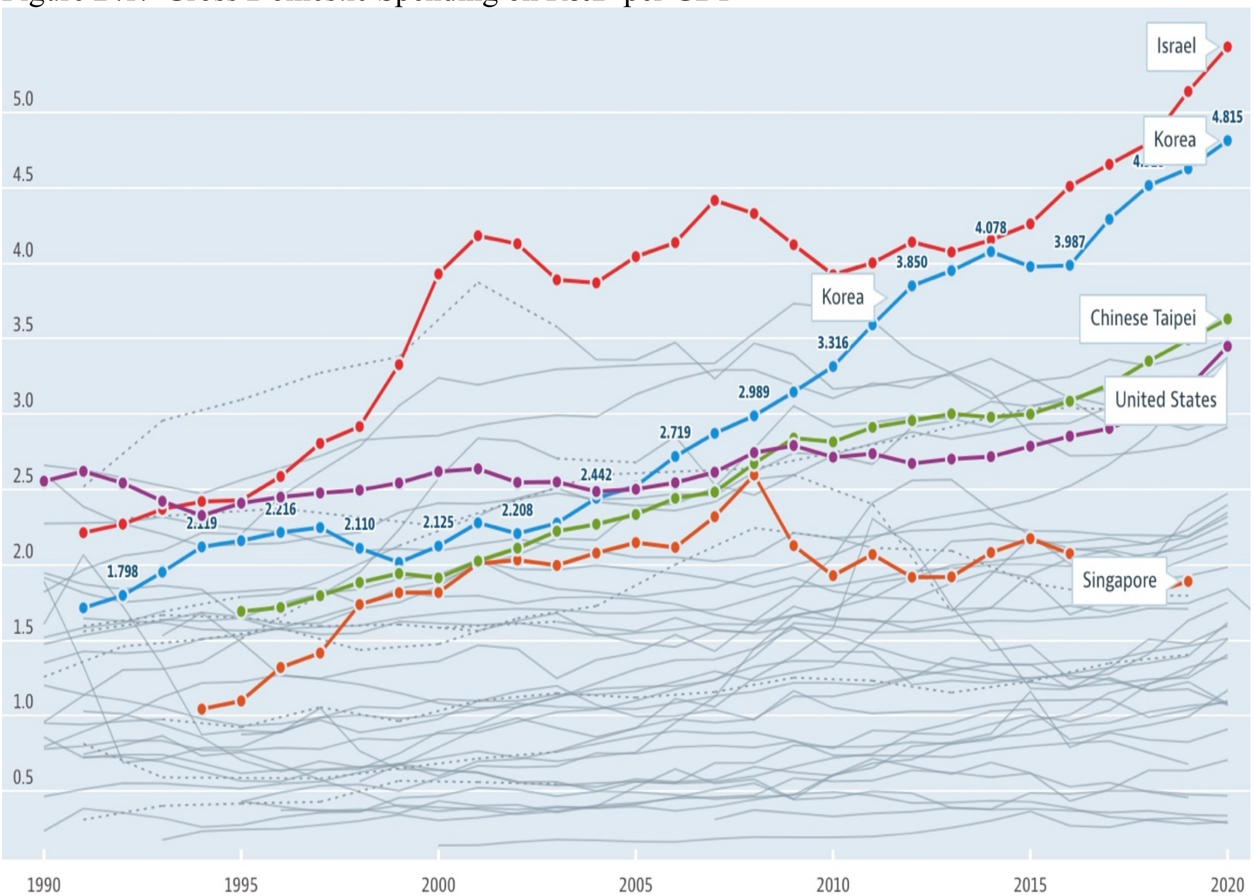
Notes. Estimates are based on the model in Equation (1.3), using firm-year observations over the period 1982-1996. The dependent variable is value-added (in log) of a firm in a given year in all columns. (Forward) indicates the weighted sum of the ratio of skilled-to-unskilled labor in the upstream industries with input coefficients as weights. I apply Levinsohn-Petrin (LP) method in column (2), (3), and (4), using direct material cost (in log) and electricity cost (in log) as proxies to unobservable productivity shock. Column (3) and (4) include year dummies, and column (4) include firm dummies. The number of firm dummies, however, exceeds the maximum number of variables in the STATA program. To address this issue, I sample 1,000 firms randomly in each trial and apply the LP method. I iterate 1,000 trials and collect 1,000 sets of coefficients. I go on to calculate the mean and standard errors of each coefficient. I use the property that the expected value of sample mean is equal to population mean. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Appendix B

R&D as a Pathway from Human Capital Accumulation to Technology Adoption

B.1 Gross Domestic Spending on R&D per GDP

Figure B.1: Gross Domestic Spending on R&D per GDP



Source: OECD (2023)

B.2 Robustness Test: Levinsohn-Petrin method

Table B.1: Technology Shift : R&D-to-sales ratio, Levinsohn-Petrin method

D.V.= *Log (Value-added)*	(1) FE	(2) LP	(3) LP	(4) LP
Log (Unskilled)	0.5366***	0.1234***	0.2788***	0.3218***
	(0.0065)	(0.0056)	(0.0045)	(0.0680)
Log (Skilled)	0.2932***	0.1392***	0.2096***	0.1725***
	(0.0054)	(0.0045)	(0.0021)	(0.0499)
Log (Capital)	0.1138***	0.2328***	0.1612***	0.1392***
	(0.0037)	(0.0040)	(0.0034)	(0.0497)
Log (Unskilled)	1.3926*	-4.7389***	-8.9096***	1.1784
** R&D spillover*	(0.8399)	(0.8165)	(0.5877)	(8.8102)
Log (Skilled)	-1.4661**	1.3011**	-3.1662***	-0.8725
** R&D spillover*	(0.7408)	(0.5756)	(0.3861)	(7.5674)
Log (Capital)	1.4483***	-1.4089***	4.4404***	0.6224
** R&D spillover*	(0.4962)	(0.3163)	(0.3228)	(5.1660)
R&D spillover	-9.4215***	25.5331***	-6.4091***	-5.8356
	(2.2373)	(1.2853)	(1.44)	(23.1027)
FirmFE	Y	N	N	Y
YearFE	Y	N	Y	Y
Observations	202050	176198	176198	2481
Outcome Mean	6.1454	6.1454	6.1454	6.1454

Notes. Estimates are based on the model in Equation (2.5), using firm-year observations over the period 1983, 1988, 1993, and 1996. The dependent variable is value-added (in log) of a firm in a given year in all columns. (R&D spillover) indicates the weighted sum of the ratio of R&D-to-sales in the upstream industries with input coefficients as weights. I apply Levinsohn-Petrin (LP) method in column (2), (3), and (4), using direct material cost (in log) and electricity cost (in log) as proxies to unobservable productivity shock. Column (3) and (4) include year dummies, and column (4) include firm dummies. The number of firm dummies, however, exceeds the maximum number of variables (120000) in the STATA program. To address this issue, I sample 1,000 firms randomly in each trial and apply the LP method. I iterate 1,000 trials and collect 1,000 sets of coefficients. I go on to calculate the mean and standard errors of each coefficient. I use the property that the expected value of sample mean is equal to population mean. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.2: Technology Shift : R&D-to-production ratio, Levinsohn-Petrin method

D.V.= *Log (Value-added)*	(1) FE	(2) LP	(3) LP	(4) LP
Log (Unskilled)	0.5372***	0.1242***	0.2780***	0.3221***
	(0.0065)	(0.0042)	(0.0039)	(0.0675)
Log (Skilled)	0.2934***	0.1392***	0.2083***	0.1727***
	(0.0054)	(0.0042)	(0.0049)	(0.0494)
Log (Capital)	0.1138***	0.2313***	0.1611***	0.1392***
	(0.0037)	(0.0035)	(0.0040)	(0.0494)
Log (Unskilled)	1.3033	-5.2557***	-9.2674***	1.1447
** R&D spillover*	(0.8607)	(0.5469)	(0.7568)	(9.1061)
Log (Skilled)	-1.6018**	1.3720**	-3.0019***	-0.9747
** R&D spillover*	(0.7503)	(0.6468)	(0.7669)	(7.7809)
Log (Capital)	1.5085***	-1.0527***	4.7037***	0.6773
** R&D spillover*	(0.5038)	(0.3604)	(0.4125)	(5.3109)
R&D spillover	-9.5408***	24.0226***	-7.2049***	-5.9804
	(2.2654)	(1.6244)	(1.3661)	(23.7069)
FirmFE	Y	N	N	Y
YearFE	Y	N	Y	Y
Observations	202050	176198	176198	2481
Outcome Mean	6.1454	6.1454	6.1454	6.1454

Notes. Estimates are based on the model in Equation (2.5), using firm-year observations over the period 1983, 1988, 1993, and 1996. The dependent variable is value-added (in log) of a firm in a given year in all columns. (R&D spillover) indicates the weighted sum of the ratio of R&D-to-production in the upstream industries with input coefficients as weights. I apply Levinsohn-Petrin (LP) method in column (2), (3), and (4), using direct material cost (in log) and electricity cost (in log) as proxies to unobservable productivity shock. Column (3) and (4) include year dummies, and column (4) include firm dummies. The number of firm dummies, however, exceeds the maximum number of variables (120000) in the STATA program. To address this issue, I sample 1,000 firms randomly in each trial and apply the LP method. I iterate 1,000 trials and collect 1,000 sets of coefficients. I go on to calculate the mean and standard errors of each coefficient. I use the property that the expected value of sample mean is equal to population mean. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

Appendix C

Labor Productivity, Complementarity, and Diverging Trend of Employment between Permanent and Temporary Workers

C.1 Robustness Check: Levinsohn-Petrin method

Table C.1: Technology Shift, Levinsohn-Petrin method

D.V.= *Log (Value-added)*	(1) FE	(2) LP	(3) LP	(4) LP
Log (Permanent)	0.2771***	0.5109***	0.5153***	0.1659
	(0.0283)	(0.0145)	(0.0084)	(0.3374)
Log (Temporary)	0.0926***	0.0851***	0.0912***	0.0630
	(0.0111)	(0.0106)	(0.0112)	(0.1427)
Log (Capital)	0.1149***	0.1734***	0.1715***	0.1270
	(0.0159)	(0.0093)	(0.0101)	(0.2268)
Log (Permanent)	0.2607***	-0.0121	-0.0188*	0.1851
** Forward*	(0.0419)	(0.0283)	(0.0113)	(0.5024)
Log (Temporary)	-0.0070	0.0182	0.0138	-0.0132
** Forward*	(0.0162)	(0.0164)	(0.0163)	(0.2069)
Log (Capital)	-0.0434*	-0.1327***	-0.1277***	-0.0462
** Forward*	(0.0229)	(0.0123)	(0.0158)	(0.3137)
Forward	-1.5176***	1.0412***	1.0352***	-0.6173
	(0.3543)	(0.0566)	(0.0860)	(4.1473)
FirmFE	Y	N	N	Y
YearFE	Y	N	Y	Y
Observations	149223	126874	126874	3928
Outcome Mean	7.4354	7.4354	7.4354	7.4354

Notes. Estimates are based on the model in Equation (3.7), using firm-year observations over the period 2011-2019. The dependent variable is value-added (in log) of a firm in a given year in all columns. (Forward) indicates the weighted sum of the ratio of permanent-to-total labor in the upstream industries with input coefficients as weights. I apply Levinsohn-Petrin (LP) method in column (2), (3), and (4), using direct material cost (in log) and electricity cost (in log) as proxies to unobservable productivity shock. Column (3) and (4) include year dummies, and column (4) include firm dummies. The number of firm dummies, however, exceeds the maximum number of variables (120000) in the STATA program. To address this issue, I sample 1,000 firms randomly in each trial and apply the LP method. I iterate 1,000 trials and collect 1,000 sets of coefficients. I go on to calculate the mean and standard errors of each coefficient. I use the property that the expected value of sample mean is equal to population mean. The standard errors in parentheses are clustered at the firm level and robust to heteroskedasticity. * significant at 10%, ** significant at 5%, *** significant at 1%.

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