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DOES GROWTH LEAD TO LABOR REALLOCATION?

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ABSTRACT

I study the relationship between long-run growth and labor reallocation when incumbent producers both innovate over their previous products (own-product improvements) and expand to new product markets (product expansion). I calibrate a quality ladder model of endogenous growth with an establishment panel survey data that distinguish different innovation types. I discover that own-product improvements account for 90% of the steady-state productivity growth and 81% of the welfare gains from faster growth after R&D incentives. Since own-product improvements have smaller effects to reallocate labor between establishments, despite an increase in growth rates, labor reallocation rates barely change in response to R&D incentives.

CHAPTER 1

DOES GROWTH LEAD TO LABOR REALLOCATION?

1.1 Introduction

[1]The rates at which labor inputs are reallocated across firms—job creation rates for growing firms and job destruction rates for shrinking firms[2]—have been an informative metric to evaluate the growth potential of an economy. To be specific, labor reallocation from low- to high- productivity firms has been considered the most important force that drives aggregate productivity growth since [45]. Behind this is the idea that technological developments are made when new firms with better technologies expand to new product markets and replace old firms.

However, incumbent firms often make innovations that replace their existing products, and this type of innovation has different implications for the relationship between growth and labor reallocation. In this paper, I study how growth is related to the labor market reallocation process when both current and expanding producers can improve the quality of goods.

I define the quality improvement by current producers over their existing products as an own-product improvement and product innovation by incumbent producers expanding to new product markets as product expansion[3]. I also define product improvement made

1. This study uses the LIAB longitudinal model, version 1975-2017, of the Linked-Employer-Employee Data (LIAB) from the IAB. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access. DOI: 10.5164/IAB.LIABLM7517.de.en.v1.

2. In [17], job creation rates are defined by $2\max\{E_t - E_{t-1}, 0\}/(E_t + E_{t-1})$, and job destruction rates are defined by $2\max\{E_{t-1} - E_t, 0\}/(E_t + E_{t-1})$, where E_t is the employment of an establishment or a firm at time t.

3. In this case, the product is defined by substitutability. If a new product is a close substitute for an old product, I consider the new product being another version of the old product. If the new product does not

by new producers as entrant innovation. I argue that if innovation of current producers is dominant in productivity growth, growth is quantitatively orthogonal to labor reallocation. This is because, unlike product expansion, old jobs of current producers are not directly destroyed by new jobs created by new producers for own-product improvements. Thus, how much labor reallocation is needed for a given level of productivity growth depends crucially on which type of innovation is dominant in the economy.

To decompose the contribution of innovation types to productivity growth and labor reallocation, I use novel data about establishment-level innovation activities from a German establishment panel survey[4]. The survey asks directly whether each establishment had improved the quality of their products, upgraded production processes, and added a new product variety. The separate survey questions naturally distinguish the different types of innovations. I merge the survey data with the administrative employer-employee matched data where I can observe the number of employees at each establishment before and after the innovation events. I establish new facts about different types of innovations from this new data set.

Then, I construct an endogenous growth model with own-product improvements, product expansion, and entrant innovation to translate individual innovation choices into aggregate outcomes on productivity growth and labor reallocation. The model parameters are calibrated to match empirical moments from the survey and administrative data. The model is used to quantify the relative contribution of different innovation types. Lastly, I use the model to evaluate the impact of a recent major R&D tax incentive in Germany on aggregate growth and labor reallocation rates. The R&D incentive subsidizes R&D labor expenditures made by firms and promotes productivity growth by sending production labor to R&D

substitute the old product, the new product is considered as a separate product.

4. The unit of analysis is an establishment throughout the paper. I call establishments equivalently firms.

activities. The new policy becomes a useful structural break to see the relationship between growth and labor reallocation. Ultimately, this exercise emphasizes the importance of own-product improvements behind the relationship.

The model in this paper is a standard extension of the [34] growth model with expansion to new product lines by introducing incumbents' innovation over their own product lines, as in [5] and [24]. The model implies that for the same increase in productivity of a given product line, product expansion is associated with more labor reallocation from non-innovating firms to the innovating firm because the output produced by the replaced firm moves to the expanding firm. In other words, product expansion requires more labor reallocation across firms in order to have the same effect on productivity growth as own-product improvements.

Using the calibrated model, I conclude that own-product improvements account for more than 90% of the Balanced Growth Path (BGP) productivity growth in the German economy. Entrant innovation accounts for only 5% of the growth on the BGP, and the remaining 5% comes from product expansion. This small contribution of product expansion to productivity growth comes from two empirical moments. First, in the extensive margin, only 25% of surveyed establishments respond that they added a new product into their portfolios (product expansion), while 47% of surveyed establishments respond that they improved the quality of their existing products (own-product improvements). Second, in the intensive margin, product-expanding establishments increased their employment only by 1.9 percentage points more than the average surviving establishment two years after the innovation year, compared to establishments with own-product improvements expanding their size by additional 1.7 percentage points. Thus, the labor reallocation associated with production expansion is smaller in magnitude than the reallocation associated with own-product improvements. In theory, product expansion needs much more labor reallocation across firms to have a growth impact quantitatively similar to own-product improvements in the model because product expansion replaces operating firms on product lines. Consequently, the small amount of labor reallocation associated with product expansion implies that firm-level replacements made by product expansion do not generate much productivity growth.

Lastly, through the lens of the quantitative model, I reveal that new R&D incentives in Germany improve the welfare of the representative household by increasing productivity growth rates from more R&D activities despite a smaller output level from reducing production labor inputs in the short run. The model predicts that the initial output shrinks by 2.7% by having more R&D workers and fewer production workers. As productivity grows faster, the gap between the pre-policy and the post-policy outputs becomes smaller. The post-policy economy catches up with and exceeds the post-policy BGP after 25 years. The new growth path after the R&D incentive is welfare-improving because current innovation activities have positive externalities on future innovation. The welfare gains from faster productivity growth are equivalent to a 2% permanent increase in the consumption level of the representative household under the pre-policy scenario.

I conclude that own-product improvements generate the majority of welfare gains from faster productivity growth over the transition path. Among the three innovation margins (own-product improvements, product expansion, and entrant innovation), own-product expansion alone makes 81% of the welfare gains from faster productivity growth. Product expansion and entrant innovation barely change. Since own-product improvements do not replace producers on product lines, labor reallocation rates show negligible changes despite faster output and productivity growth.

This paper has three contributions. First, this paper discovers that technological growth is far less destructive than what has been previously thought in the literature. This conclusion is consistent with [24] but uses a different calibration strategy. They estimate the frequency of own-product improvement and product expansion rates by matching the panel distribution of establishment-level annual employment growth rates. Not having innovation measures, they assume that all establishment-level employment adjustments come from technological improvements. Given that most establishment-level adjustments are small-sized, they conclude that most technological changes are incremental, which do not generate establishment-level creative destruction. I use a direct measure of innovation activities, match additional employment growth rates after innovation activities, and learn that product expansion has a negligible impact on aggregate productivity growth. Moreover, technological shocks at the establishment level generate only about 20% of the actual labor reallocation rates in the data. Thus, it can be misleading to attribute all idiosyncratic employment changes to technology-driven forces.

This finding is in sharp contrast to the existing studies using growth models with quality ladders—where for a product line to be improved, there must be an external firm that replaces the current firm. A seminal paper by [4] models innovation as firms competing against each other to occupy a limited number of products. Most firm-level innovation papers, such as [34], [39], and [1], follow this tradition and therefore assume that all technological growth comes from product expansion promoting competition across firms. As noticed in [2] and [5], incumbents can make less destructive innovations by improving their previous products. I follow their way of modeling non-destructive innovation and argue that innovations are more incremental than previously thought.

Second, this paper contributes to discussions on the aggregate effect of innovation on employment. Theoretical papers on this issue make different predictions depending on whether destructive innovation sends replaced workers to the unemployment pool or new employers[43, 42, 40]. Empirical results also give mixed evidence on the importance of destructive innovation to explain employment differences across countries and over time[14, 16, 29, 21]. In the declining business dynamism literature, [18, 19] discuss that the lower degree of entrant innovation in the U.S. is the key factor for slower labor reallocation in the U.S. Using a more direct measure of innovation, the findings in this paper suggest that innovation does not increase unemployment quantitatively because most innovation is made by incumbents to improve their own products.

Lastly, to my knowledge, this is the first paper that incorporates survey-based measures of innovation into the structural analysis of economic growth. Economists often rely on indirect inference methods to back out innovation behavior or productivity shocks from other establishment-level behaviors such as employment, output, and wage [39, 15, 24]. Other studies use the patent application, grant, or citation data to measure the innovation activities of a sector or a firm, assuming that the new knowledge made by a patent is embedded exclusively in the firm owning the patent [3, 35, 5, 20, 33]. Papers on knowledge spillovers also use patent data to measure innovation [10, 30, 13].

This paper uses a survey-based measure of innovations that captures more extensive innovation activities behind the knowledge frontier, making it easier to distinguish different innovation activities[5]. Survey-based measures of innovation are recently getting attention in economics. [46] propose to use a new module on innovation activities in the 2018 Annual Business Survey to measure advanced technology adoption such as cloud computing and artificial intelligence. Although patents are a suitable source of information for innovation activities at the knowledge frontier, they are less relevant when measuring the adoption and imitation activities of market laggards. Moreover, different survey questions are a useful

5. In Online Appendix 1.B.2, I compare the number of external and internal patents, as defined in [5], to the survey-based measure of innovations.

device to distinguish different innovation activities.

This paper is organized as follows. In Section 1.2, I build a quantitative model of endogenous growth through innovation choices. In Section 1.3, I describe the German establishment panel survey and explain how model parameters are calibrated from empirical moments in the German data. In Section 1.4, I evaluate the model fit and decompose the contribution of different innovation types to growth and labor reallocation. Lastly, in Section 1.5, I use the calibrated model to quantitatively show the effect of the R&D tax incentives.

1.2 Growth Model with Quality Ladder

I construct a model as a framework to quantify the effects of innovation decisions at the firm level on aggregate outcomes such as productivity growth and labor reallocation rates. At the firm level, own-product improvement and product expansion choices are endogenized and aggregated to generate productivity growth as in [5]. The idiosyncratic innovation process at the product-line level generates endogenous dispersion of product qualities across production lines as in [1].

I focus on the balanced growth path (BGP) equilibrium where the interest rate is constant, the final output and the wage grow deterministically at a constant rate, g_Y, the relative productivity of a product line depreciates at a constant rate, g_x, and the value and the distribution over x are time-invariant. Thus, the time subscript t is omitted when the object is not changing over the BGP.

1.2.1 Environment

The economy consists of representative households and firms that produce either final or intermediate goods. Representative households make a labor supply decision, gather all labor income and business profits, and decide the consumption path. Representative households also consume homogeneous final goods—and the production of the final goods does not require any labor input. Final goods are competitively produced by combining differentiated intermediate goods. Each intermediate good variety corresponds to a product line and is produced by firms operating on the product line. Products on the same product line are perfectly substituted after adjusting their quality differences; products over different product lines are imperfectly substituted. Production of intermediate goods relies on labor inputs traded in the competitive and frictionless labor market.

Firms producing intermediate goods are heterogeneous with respect to their product line portfolios. They can hold more than one product line, and each product line has an idiosyncratic relative quality level, denoted by x. Because of the aggregate growth, the relative productivity of each product line depreciates over time without any innovation behavior, which is described in more detail below.

Firms can improve their existing product lines. Own-product innovation choice is specific to each product line. They choose a Poisson rate for an own-product improvement, ξ, and hire $c_{own}(\xi)$ units of labor per unit of time on a product line. This labor cost is convex in the rate of innovation, i.e., $c'_{own}(\xi), c''_{own}(\xi) > 0$. If they succeed in making such innovation on a product line, the relative quality of the product line jumps by $\lambda\bar{x}$ instantaneously, where $\bar{x}$ is the cross-sectional mean of x. Own-product improvements do not affect the number of product lines held by the firm.

Firms also expand to new product lines with a Poisson rate ζ by hiring $c_{exp}(\zeta)$ amount of labor per unit of time on a product line. The cost of innovation is also convex, i.e. $c'_{exp}(\zeta), c''_{exp}(\zeta) > 0$. Conditional on the product expansion event, a firm is matched to a vacant product line with probability p. The productivity of the firm on the new product line is simply the current productivity of the product line on which the product expansion is based. Without any competitors, the firm starts producing on the vacant line.

With probability $1 - p$ conditional on a product expansion event, firms are matched with a product line that is currently occupied by another firm. As in [5], I assume that the expanding producers play a two-stage Bertrand game with existing producers on the product line. In the two-stage Bertrand game, all producers on the product line pay $\epsilon > 0$ to proceed to the second stage in the first stage. In the second stage, only the firms that paid in the first stage can set their price and sell in the market. In the Subgame Perfect Nash Equilibrium, only the best quality producer pays in the first stage and sets the monopolist price in the second stage.

As a result of the Bertrand game, only the best quality producer operates on a product line at the monopolistic price, meaning that the expanding firm can successfully catch the production opportunity only if it is more productive than the current occupier of the matched product line. Let $F(x)$ denote the probability that the firm expanding on a product line with productivity x is more productive than randomly matched product lines. With undirected random matching, $F(x)$ is the cumulative distribution function of the relative product line quality, x. Consequently, $p+(1-p)F(x)$ is the probability that the firm gains a new product line after product expansion.

One implication of this Bertrand game is that the markup charged by the most productive firm is not affected by the quality level of the competitors. [41], for example, assumes that the markup of the most productive firm increases with the technology gap between the leading firm and competitors. Then, the endogenous markup structure has additional implications for the static efficiency of the economy. Without a clear empirical answer on whether markups increase with the technology gap in the German case, I abstract away from this possibility and assume that the quality difference across producers within a product market is orthogonal to the price setting behavior.

A firm loses a product line when either an expanding firm or an entering firm is matched to the product line and is more productive. The Poisson rate of this event is denoted by $\tau(x)$, and $\tau'(x) > 0$. For tractability, this loss of a product line is assumed to be permanent. Consequently, even if the producer with the best quality on the line disappears, the producers with lower qualities cannot operate on the product line again.

A firm exits the market in the two cases. First, a firm exits the market at an exogenous rate δ. In this case, all product lines held by the exiting firm are left vacant and are subject to being matched with expanding and entering firms instantaneously. The probability of being matched with a vacant product line after product expansion, p, is determined by the mass of exogenously exiting firms versus the mass of expanding incumbents and entrants. Second, a firm exits the market if the firm had only one product line and if that product line is poached by another firm.

Entering firms start with one product line. An entering firm first randomly meets a product line to learn and improves their own quality based on the matched product line with the same step size $\lambda\bar{x}$. It also meets a vacant product line with the same probability as the product expansion, p, and starts producing on the matched product line. With probability $1 - p$, it meets an occupied product line. As in the product expansion case, the entrant can produce on the occupied product line only if it is more productive than the firm currently operating on the product line.

1.2.2 Values

The state variable of a firm is the set of productivity levels on product lines it occupies, $\{x_j\}_{j=1}^{N_i}$, where N_i is the number of product lines held by the firm and x_j is the relative quality[6] of the product line. The revenue of this firm per unit of time is $\sum_{j=1}^{N_i} \pi(x_j)$. Since all decisions are product line specific and the revenues from product lines are additively separable, the total firm value is the sum of product line values. Furthermore, on the BGP, the value of a product line is a product between the time-invariant value that only depends on the relative quality and the aggregate output. Appendix 1.A.2 shows the formulation of the firm-level value function as well as the multiplicative separability of product-line values between the aggregate component Y_t and the time-invariant function of the relative quality level, $v(x_j)$. To summarize, the firm value $\mathfrak{V}\left(\{x_j\}_{j=1}^{N_i}, W_t, Y_t\right)$ can be expressed in the following form on the balanced growth path.

$$\mathfrak{V}\left(\{x_j\}_{j=1}^{N_i}, W_t, Y_t\right) = Y_t \sum_{j=1}^{N_i} v\left(x_j\right)$$

The time-invariant component of the product line value, $v(x)$, is given by the following Hamiltonian-Jacobi-Bellman (HJB) equation.

6. This can also be interpreted as the relative productivity because of the isomorphism between quality and inverse productivity in the Constant Elasticity of Substitution (CES) demand structure with the Constant Return to Scale (CRS) technology.

$$
\begin{aligned}
(\rho + \delta + \tau(x))\, v(x) = \max_{\xi,\zeta \geq 0} \Bigg\{ & \pi(x) - g_x x v'(x) \\
& - w c_{own}(\xi) + \xi \Big(v(x + \lambda \bar{x}) - v(x) \Big) \\
& - w c_{exp}(\zeta) + \zeta (p + (1-p) F(x))\, v(x) \Bigg\}
\end{aligned}
\tag{1.1}
$$

In this equation, ρ is the discount rate, $w = W_t/Y_t$ is the wage rate relative to the final output (which is constant over the BGP), δ the exogenous exit rate, $\tau(x)$ the creative destruction rate, $\pi(x)$ the revenue defined below, $c_{own}(\xi)$ the own-product improvement cost, and $c_{exp}(\zeta)$ the product expansion cost.

An own-product improvement increases the relative quality of the product line with constant step size, $\lambda\bar{x}$. Product expansion adds a new product line with the same quality by probability $p + (1-p)F(x)$. The product expansion rate is unambiguously increasing in x because the value is increasing in x. The own-product improvement rate is not monotone in x but tends to increase in x when x is low—this is because the potential return to product expansion is increasing faster with a higher probability of a successful expansion through a higher $F(x)$. Let $\xi(x)$ and $\zeta(x)$ denote the rates of own-product improvements and product expansion chosen by firms on the product line with x, respectively.

1.2.3 Entry

Like own-product improvements and product expansion, entrant innovation also requires labor inputs. Entrants must hire $c_{entry}(\chi)$ units of labor to draw the quality of a product line to learn and enter the market as described in Section 1.2.1. The free entry condition determines the rate of firm entry, χ.

$$wc_{entry}(\chi) = \chi\left(\int (p + (1-p)F(x+\lambda\bar{x}))v(x+\lambda\bar{x})dF(x)\right) \tag{1.2}$$

The cost per entry, $c_{entry}(\chi)/\chi$, is increasing in χ.

1.2.4 Final Goods

Homogeneous final goods are competitively produced by aggregating intermediate goods over different product lines with the constant elasticity of substitution. The final good is the numeraire.

$$Y_t = \left(\int_0^1 a_{jt} y_{jt}^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}}$$

$\sigma > 1$ is the elasticity of substitution, a_{jt} is the absolute quality of the intermediate good from product line j at time t, and $j \in [0,1]$ is the normalized set of product lines. As described in Section 1.2.1, only the firm with the highest quality operates on a product line j in equilibrium.

A monopolistic firm takes the demand of final producers as given and sets a price that maximizes the revenue. The quality of the firm shifts the demand curve to the right but does not affect the demand elasticity (and thus has no impact on the mark-up). The price-setting problem is described in the following equation.

$$p_{jt} = \arg\max_{p_{jt}} \left\{ y_{jt}p_{jt} - W_t y_{jt} \right\},$$

subject to

$$y_{jt} = a_{jt}^{\sigma} Y_t P_t^{\sigma} \left(p_{jt}\right)^{-\sigma}$$

$P_t := \left(\int_0^1 a_{jt}^{\sigma} p_{jt}^{1-\sigma} dj\right)^{\frac{1}{1-\sigma}}$ is the quality-adjusted average input price index, and W_t is the wage for unit labor. In equilibrium, $P_t = 1$ for zero-profit of final good producers. The labor productivity is normalized to one on all product lines so that one labor unit is converted to one unit of intermediate goods[7]. The monopolists' pricing follows a simple constant mark-up rule, $p_{jt} = \sigma/(\sigma - 1)W_t$. In equilibrium where all prices are set by this rule, the zero-profit condition for final good producers can be written as

$$\frac{\sigma}{\sigma - 1} W_t = A_t := \left(\int_0^1 a_{jt}^{\sigma} dj\right)^{\frac{1}{\sigma - 1}}.$$

Thus, in equilibrium, the wage must increase with the average quality index, A_t, in the economy. Aggregating individual labor demand for production yields the following equation.

$$L_t^p = Y_t A_t^{-1}$$

L_t^p denotes the aggregate labor demand for production. Thus, for a fixed production labor input, Y_t increases linearly in A_t. Consequently, in a BGP equilibrium where the quantity of labor supply is fixed and Y_t increases at a constant rate, W_t increases linearly in Y_t. In

7. This specification is isomorphic to a case with production efficiency improvements. For this reason, I included both quality improvement and process innovation in my definition of own-product improvements in the empirical analysis.

this case, I can define the value-added only as a function of relative quality, x_{jt}.

$$\pi_t(x_{jt}) = Y_t \pi(x_{jt}) := Y_t \frac{x_{jt}}{\sigma}$$

In this function, $x_{jt} := a_{jt}^{\sigma}/A_t^{1-\sigma}$[8][9]. It can be further shown that the production labor input demand is also linear in x_{jt}.

It is worth noting that all profits and prices are homogeneous of degree one in the aggregate output Y_t on the BGP and that all idiosyncratic choices of product lines are determined only by the relative quality level x_{jt}. These properties make the BGP equilibrium tractable.

1.2.5 Distribution

The distribution of product lines across the relative quality, x, is characterized by the following equation.

$$\begin{aligned} g_x x f(x) = \delta F(x) + \int_{s \in (x-\lambda, x]} \xi(s) dF(s) \\ + (1-p)(G(\infty) - G(x))F(x) - pG(x) \\ G(x) := \int_{s \leq x} \zeta(s) dF(s) + \int_{s \leq x - \lambda} \chi dF(s) \end{aligned} \tag{1.3}$$

The set of product lines is normalized to the unit interval. For the derivation, see Appendix 1.A.4.

The probability of expanding and entering firms to meet a vacant line, p, is given by the

8. This definition of x_{jt} implies that $\bar{x} := \int x_{jt} dj = 1$. Thus, I omit $\bar{x}$ in the equations below.

9. Own-product improvements increase the quality of the product line with a_{jt} by some step size so that the innovation step size is constant in the relative quality x_{jt}. See Appendix 1.A.3 for the explanation and the mapping between the step sizes.

condition that the mass of the product lines left vacant due to exogenous exits is equal to the mass of expanding and entrant firms that are matched to vacant lines.

$$\delta = p \int \zeta(s) dF(s) + \chi p \tag{1.4}$$

The creative destruction rate, $\tau(x)$, satisfies the following equation, which implies that the rate at which incumbent firms are taken out from their product lines by creative destruction is equal to the rate at which expanding firms poach new product lines.

$$\tau(x) = (1-p)\left(\chi\left(\int_{s>x-\lambda} dF(s)\right) + \int_{s>x} \zeta(s) dF(s)\right) \tag{1.5}$$

The output growth rate, g_Y is linear with the depreciation rate for x on the BGP.

$$g_Y = (\sigma - 1) g_x$$

Appendix 1.A.5 describes the expression for g_x in the BGP equilibrium.

1.2.6 Market Clearing

The final good market is cleared if $C_t = Y_t = A_t L_t^p$. Labor inputs are used for production and R&D activities such as own-product improvements, product expansion, and entrant innovation. The total expenditure on labor is given by the following equation.

$$W_t L_t = \frac{\sigma - 1}{\sigma} Y_t + W_t \int c_{own}(\xi(x)) dF(x) + W_t \int c_{exp}(\zeta(x)) dF(x) + W_t c_{entry}(\chi)$$

On the BGP, wage and output grow at the same rate. Thus, the labor market clearing condition becomes:

$$wL = \frac{\sigma - 1}{\sigma} + w \int c_{own}(\xi(x))dF(x) + w \int c_{exp}(\zeta(x))dF(x) + wc_{entry}(\chi).$$

1.2.7 Equilibrium

The Balanced Growth Path (BGP) equilibrium is defined as the value function $v(x)$; the policy functions $\xi(x)$, $\zeta(x)$; the product line distribution $f(x)$; the creative destruction rate $\tau(x)$; the probability of meeting a vacant product line p; the depreciation and the growth rates g_x and g_Y; the entry rate χ; the constant wage rate relative to the output w; the constant interest rate r; and the constant labor supply L such that the following conditions hold.

1. The value and the policy functions satisfy Equation (1.1).
2. The distribution of product lines over x stays constant and satisfy Equation (1.3). The mass of the product lines is also time-invariant[10].
3. Equation (1.2) holds to pin down χ.
4. Growth and creative destruction rates are internally consistent, as in Equations (1.5) and (1.9).
5. The final goods, the intermediate goods, and the labor markets are cleared as in Section 1.2.6.

10. If $\zeta(x)$ and χ are too small, the mass of available product lines may get lower over time because of net product line loss after exogenous firm exits. I am restricting the value of c_{entry} and c_{exp} such that this does not happen and the mass of available product lines is constant over time.

6. The representative household optimizes[11].

1.2.8 Innovation and Labor Reallocation

Both types of incumbent innovation (own-product improvements and product expansion) lead to productivity growth. However, they have quantitatively different implications for labor reallocation across firms. To show this, I compare a productivity increase of a product line from product expansion to an increase from an own-product improvement.

Firm-level employment is expressed as the sum of employment size over product lines held by the firm. Employment at the product line level is determined by the relative quality level x.

$$l(x) := \frac{\sigma - 1}{\sigma}\frac{x}{w} + c_{exp}(\zeta(x)) + c_{own}(\xi(x))$$

The employment on each product line, $l(x)$, has two components: production and R&D labor. The production labor is linearly increasing in the relative quality x. The R&D labor for product expansion $c_{exp}(\zeta(x))$ is also increasing in x because the return to product expansion is increasing in relative quality. The R&D labor demand for own-product improvement does not have an unambiguous relationship to x but numerically tends to increase in x because of higher returns to product expansion and lower creative destruction rates.

If an own-product improvement happens to a product line with x, the innovating firm on

11. The representative household's optimization fixes the interest rate over the BGP and determines the labor supply curve. See Appendix 1.A.1 for the set-up.

the product line hires the following amount of additional labor inputs.

$$l(x+\lambda) - l(x) = \lambda\frac{(\sigma-1)}{w\sigma} + \big(c_{exp}(\zeta(x+\lambda)) - c_{exp}(\zeta(x))\big) \\ + \left(c_{own}(\xi(x+\lambda)) - c_{own}(\xi(x))\right) \tag{1.6}$$

The first term on the left-hand side of Equation (1.6), $\lambda(\sigma-1)/\sigma$, is the increase in employment from a shift in the demand curve for the intermediate input variety with better quality. At the same time, the returns to innovations change. Consequently, the R&D labor demand also changes. As mentioned above, R&D inputs for the product expansion unambiguously increase, but R&D inputs for own-product improvements may either increase or decrease. Still, because production and product expansion labor demands are increasing in x, labor is reallocated toward firms that improve the quality of their existing products. Non-innovating establishments in the economy reduce their labor input because of the depreciation of their relative quality.

Suppose that a product line experiences product expansion with the same amount of a productivity increase from x to $x+\lambda$. Then, the new firm on the product line newly hires $l(x+\lambda)$ amount of labor inputs, while the old firm loses $l(x)$ amount of labor. Other non-innovating firms experience the same degree of relative quality depreciation because the change in average quality remains the same. Thus, product expansion generates an additional $l(x)$ amount of labor reallocation across firms conditional on the same productivity increase of a product line.

On the BGP, for a sufficiently small time interval Δ, product lines create jobs in three cases[12]: own-product improvement, product expansion, and entry. Firms improving their

12. For a small Δ, only one of the events happens to a product line.

own products increase employment by $l(x+\lambda) - l(x) - \Delta g_x x l'(x)$, product-expanding firms increase employment by $l(x) - \Delta g_x x l'(x)$, and entrant firms create jobs by $l(x+\lambda)$. The quality depreciation term, $\Delta g_x x l'(x)$, applies to all incumbents regardless of their innovation status. Then, the (net) job creation at the product line level can be approximated as the following equation.

$$
\begin{aligned}
JC := & \underbrace{\int \Delta\xi(x)(l(x+\lambda) - l(x) - \Delta g_x x l'(x))dF(x)}_{\text{own-product improvement}} \\
& + \underbrace{\int \Delta\zeta(x)(p + (1-p)F(x))(l(x) - \Delta g_x x l'(x))dF(x)}_{\text{product expansion}} \\
& + \underbrace{\int \Delta\chi(p + (1-p)F(x+\lambda))l(x+\lambda)dF(x)}_{\text{entrant innovation}}
\end{aligned} \tag{1.7}
$$

Thus, increases in $\xi(x)$ and $\zeta(x)$ subsequently increase more jobs by having more firms innovate and create jobs. However, more innovations also increase g_x, which accelerates the depreciation of the relative quality and reduces job creation of firms with innovation. Quantitatively, for the same increase in g_x, product expansion creates more jobs than an own-product improvement. Thus, product expansion is more likely to increase the aggregate amount of job creation, which is the same as the amount of job destruction on the BGP.

1.3 Calibration

1.3.1 Data

I use German establishment panel data to measure the two innovation activities—own-product improvement and product innovation—directly. The data is from the IAB Establishment Panel Survey (IAB-BP), a representative establishment survey of the Research Data Centre (FDZ) in Germany. The survey contains around 17,000 observations per year and is implemented annually from 1993 for Western Germany and 1996 for Eastern Germany. The data contains a wide range of establishment-level information about employment, hire, separation, wage, business volume, investment, and innovation activities. The survey data can be merged with the administrative employer-employee matched data set—the Linked Employer-Employee Data from the IAB (LIAB)—using the common establishment identifier. In order to reduce measurement errors, I focus on the number of employees as of June 30 in the administrative data set as my measure of establishment size.

The notion of establishments in the German data is modestly different from the U.S. Census Bureau's concept of establishments. In the U.S., establishments are distinguished by their physical location. In Germany, however, a common establishment code is shared by multiple workplaces at different locations if they belong to the same company, are physically located in the same municipality, and have the same economic class. Still, a company holds different establishment codes across different municipalities and economic classes.

Common challenges with establishment survey data are under-representation of entering establishments and attrition of establishment samples that are not related to the actual establishment exits. Because of these issues, I use the sampling weights made by the data provider and focus on the establishments that survive in the survey.

The two measures of innovation activities are derived from the answers to the following questions in the survey[13].

1. **Own-product Improvement**: In the last business year, did your establishment improve or further develop a product or service which had previously been part of your portfolio (Quality Improvement)? Or, did you develop or implement procedures in the last business year of 2015 which have noticeably improved production processes or services (Process Innovation)?

2. **Product Expansion**: In the last business year, did your establishment start to offer a product/service that had been available on the market before?

The process innovation question in the survey is included to measure an own-product improvement activity because a productivity increase on a product line is isomorphic to a quality increase in the model. These innovation variables are surveyed consistently starting from 2008; because of this, I use observations from 2007 (2008 survey) to 2017 (2018 survey). All establishment-level observations on innovation activities are weighted by the product between employment size and cross-sectional weight constructed by the data provider.

Table 1.1 shows the intensities of the two innovation types, i.e., the fraction of establishments with positive answers to the innovation questions. All establishment-level observations are pooled across years[14]. Establishments are grouped by their sizes, and the size is defined by the number of employees measured two years before the survey[15].

13. The innovation module of IAB-BP has four distinct questions on the innovation activities of which the three are included. For the description of all the questions, see Online Appendix 1.B.1.

14. In Online Appendix 1.B.1, I show the number of innovation years for each establishment. There exists a substantial heterogeneity (i.e., most establishments do not innovate at all while some establishments innovate every year). As a result, the intensities of own-product improvements and product expansion before and after innovation events in year 0 are substantially higher than the average innovation intensities. These correlation statistics are also described in Online Appendix 1.B.1.

15. The survey asks about innovation activity in the previous year of the survey. As a result, the relevant

Table 1.1: Innovation Intensity across Lagged Size Groups (%)

	All	Small	Medium	Large
Own-Product Improvement	47.2	36.5	46.8	59.1
Product Expansion	25.5	19.6	24.7	32.6

Notes: Innovation intensity is the fraction of workers in establishments with positive answers to the survey questions. Small, Medium, and Large are the first, the second, and the third tertile groups of the lagged employment size two years before the survey. All samples are weighted by their lagged employment size and sampling weights. Samples are pooled across different years.

Overall, more establishments are engaged in own-product improvements than product expansion. However, these two types of innovation are partially synchronized since the fraction of establishments that experienced own-product improvements is close to the fraction of establishments that experienced either type of innovation, or both. Larger establishments are more likely to experience both own-product improvement and product expansion than smaller establishments.

To infer the quantitative effect of surveyed innovation, I show how establishments grow after innovation events in the survey. Moments about employment growth rates after own-product improvements and product expansion (relative to the average establishment) enter the calibration exercise as targeted moments in Section 1.3.2. Nonetheless, these moments are calculated in the same way across the model and the data. For more properties of surveyed innovation activities, see Online Appendix 1.B.3.

The establishment-level employment growth rate over n periods before (-) and after (+)

predictor for the innovation probability is the employment size as of June 30 two years before the survey. When the establishment does not have the information on the previous employment size, it is omitted from the samples used in Table 1.1.

the innovation year is defined similarly as in [17].

$$EmpGr_{it}^{n-} = 2 \times \frac{AdmSize_{it} - AdmSize_{it-n}}{AdmSize_{it} + AdmSize_{it-n}}$$
$$EmpGr_{it}^{n+} = 2 \times \frac{AdmSize_{it+n} - AdmSize_{it}}{AdmSize_{it+n} + AdmSize_{it}}$$

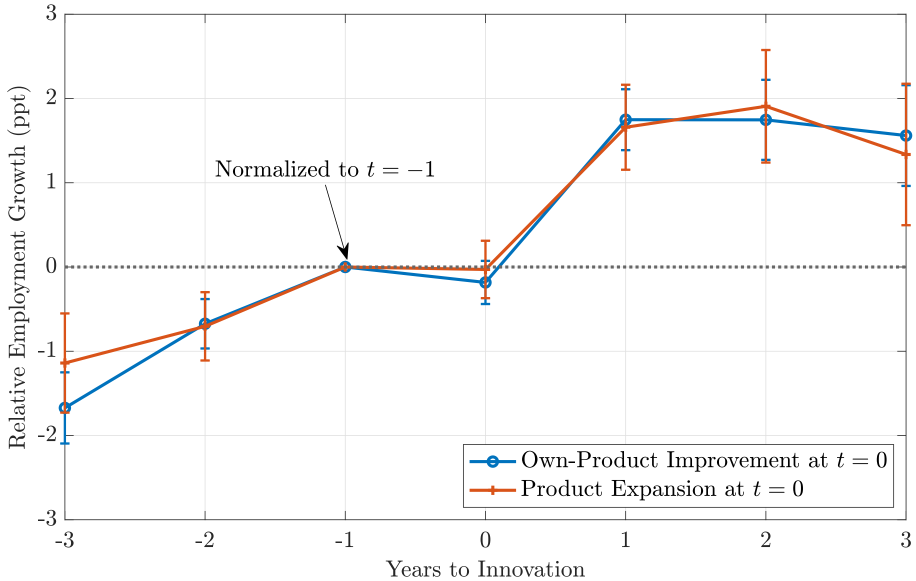
$AdmSize_{it}$ is the employment size of establishment i in year t reported via the administrative data set. Growth rates range from -2 to 2. Because of the sample attrition issue described above, I include only establishments continuing in the sample. Thus, all entrant and exiting establishments are excluded from the analysis.

To control for time trends in employment for all surviving establishments, I normalize the growth rates of innovating establishments with the growth rates of all surviving establishments. I first calculate the means for $EmpGr_{it}^{n+,-}$ among all establishments and all years in the sample. Then, I calculate the means for $EmpGr_{it}^{n+,-}$ among establishments product-improving and product-expanding in a given year t. Samples in all years are pooled to take the average. Each observation is weighted by the initial weight multiplied by its initial size[16]. I adjust the growth rates of establishments with innovation events by subtracting the average growth rate of surviving establishments in the sample. I further normalize the rates by subtracting the relative growth rates in the previous year of the innovation from all relative growth rates. Then, the normalized relative growth rate becomes zero one year before an own-product improvement and product expansion.

Figure 1.1 shows the relative employment growth rates over $n = -3, \ldots, 3$ before and after innovation events. The establishments already had steeper size growth than average establishments before the innovation event. Online Appendix 1.B.1 shows that establishments

16. Initial weight or size means their weight or size in $t - n$ for $n-$, and their weight or size in t for $n+$.

Figure 1.1: Employment Growth before and after Innovation - Data



Notes: Y-axis is the cumulative employment growth rates from year 0 calculated among establishments innovating in a given year (0) relative to the average establishment surviving in the data. The relative growth rate is normalized to be 0 in the previous year of the survey.

that innovate in year 0 are more likely to have additional innovation experiences in other years, implying the pre-trends in employment growth partly come from previous innovation activities. However, the difference between the growth rates of innovating establishments and the average establishment becomes more distinct after the innovation year. Also, the regression analyses in Online Appendix 1.B.3 reveal that innovation events are still associated with establishment growth even after controlling for establishment fixed effects.

In the calibration, I use the growth rates between the previous year of the innovation and two years after the innovation. I use the three-year gap to address the misalignment between the timing of innovation in the survey and the timing of employment measures in the administrative data set. Specifically, the panel survey asks about innovation activities in the previous calendar year of the survey, while employment measures are given as of June 30 of a year. Therefore, it is ambiguous whether the innovation that implemented a quality improvement in the year 2015 has employment measured on June 30, 2015, before or after the innovation event of 2015. Thus, while I call 2015 the innovation year, the growth rate in the innovation year can measure employment growth both before and after the innovation event. Moreover, product-expanding establishments grow faster even after the innovation year in Online Appendix 1.B.3. Nonetheless, in Figure 1.1, most size increases after innovation happen between the innovation year and the following year while there is no size growth between the innovation year and the previous year.

1.3.2 Calibration Strategy and Results

For calibration, I assume the following isoelastic innovation cost functions.

$$
\begin{aligned}
c_{own}(\xi) &= c_{own}\frac{\epsilon_{own}}{\epsilon_{own}+1}\xi^{\frac{\epsilon_{own}+1}{\epsilon_{own}}} \\
c_{exp}(\zeta) &= c_{exp}\frac{\epsilon_{exp}}{\epsilon_{exp}+1}\zeta^{\frac{\epsilon_{exp}+1}{\epsilon_{exp}}} \\
c_{entry}(\chi) &= c_{entry}\chi^{\frac{\epsilon_{entry}+1}{\epsilon_{entry}}}
\end{aligned}
$$

As ϵ_{own}, ϵ_{exp}, and ϵ_{entry} become larger, the innovation cost functions become less convex. As a result, the innovation choices respond more elastically to the changes in underlying returns to innovation and innovation subsidies. Thus, I call these parameters the elasticities of innovation.

I include additional parameters, q_{exp} and q_{own}, that govern the probability of a successful innovation given positive answers to survey questions about product expansion and own-product improvements, respectively. These parameters, especially q_{own}, are needed to match the small employment growth after product expansion. The [34] assumption that the number

Table 1.2: Externally Calibrated Moments

Moment	Meaning	Value	Source
$12 \times \rho$	Discount Rate (%)	3	Real Interest Rate
$12 \times \delta$	Exogenous Exit Rate (%)	1	Fackler et al. (2013)
$12 \times \chi$	Entry Rate (%)	1.2	Employment Share of Entrants
ϵ_{own}	Own-Product Improvement Elasticity	0.33	Innovation Cost Regression
ϵ_{exp}	Product Expansion Elasticity	0.62	Innovation Cost Regression
$\bar{L}$	Labor Supply in the Steady State	0.70	Wage = 1

Notes: All rates are annual.

of product lines takes only an integer value implies that the employment size growth after a successful product expansion is excessively large. For example, if an establishment has one product line and successfully expands to another product line, the employment size growth is 100%. In the data, product-expanding establishments grow by additional 1.9 percentage points compared to the average establishment. So, I match one positive answer to the product expansion question with additional q_{exp} product lines, not one product line, to the establishment.

The moments in Table 1.2 are transferred directly into the numerical model. The discount rate of the representative household, ρ, is calibrated such that the interest rate $r = \rho + g_Y$ is equal to 3% a year. The exogenous exit rate, δ, comes from [22] to match the exit rate of an establishment with an employment size of 100 or more. The quantity of labor supply on the BGP is calibrated to normalize the wage level on the BGP to one.

On the BGP, the elasticity and the shifter of entry costs are not identified separately with a single flow rate. As a result, I first calibrate χ, back out c_{entry} from assumed values of ϵ_{entry}, and implement the application exercise below. The entry rate on the baseline BGP, χ, is set to match the entrant share of innovation, 1.2% per year. In the administrative data, about 1.9% of employment is from establishments whose establishment identifiers appear for the first time in the last year. [27], however, shows that about one-third of establishment entries, weighted by employment, are likely to be identifier changes of existing establishments. Thus, I adjust the entry rate accordingly.

The values of innovation elasticities—ϵ_{own}, ϵ_{exp}, and ϵ_{entry}—come from estimated innovation cost functions. Studies using patents, such as [5] and [1], use the quadratic innovation cost function estimated in [9] and assume unit elasticity. In my case, I cannot guarantee the R&D cost function for patents has the same curvature as the R&D cost functions for the surveyed innovation measures. I perform a similar exercise as [9] by running the following right-censored Poisson regression.

$$\begin{aligned} N_{it}^{j} \sim & Poisson\left(\left(\frac{\epsilon_j}{\epsilon_j + 1}\right)\log(R\&DLabor_{it-1}) + \gamma_t + \varepsilon_{it}\right) \\ \bar{N}_{it}^{j} = & \min\{1, N_{it}^{j}\} \end{aligned} \tag{1.8}$$

N_{it} is the number of product innovation events of type $j = \xi$ (own-product improvement) or ζ (product expansion) that establishment i experienced in year t, $R\&DLabor_{it-1}$ is the surveyed number of R&D workers at establishment i at time t, and γ_t is the year fixed effect. The number of innovation events that are observable to an econometrician, $\bar{N}_{it}$, is right-censored at one because of how the questions are asked.

Since it is hard to distinguish how many R&D workers are assigned to own-product improvements versus product expansion, I use sectoral heterogeneity to separate convexities across different innovation types. Among manufacturing industries, the consumer goods sector has a relatively high intensity for own-product improvements (56%) but a low intensity for product expansion (28%). On the other hand, the food & beverage sector has relatively a high intensity for product expansion (48%) but a low intensity for own-product improvements (64%). Thus, I assume all R&D workers in the consumer goods sector are used for own-

Table 1.3: Internally Calibrated Moments

Moment	Data	Model	Parameter
Growth Rate (%)	1.4	1.4	λ
Fraction of Own-product Improvement (%)	47.2	46.8	c_{own}
Fraction of Product Expansion (%)	25.5	25.7	c_{exp}
Employment Growth (Own Improvement - Average, ppt)	1.7	1.7	q_{own}
Employment Growth (Expansion - Average, ppt)	1.9	1.9	q_{exp}
Employment Growth (No Innovation - Average, ppt)	-2.3	-2.8	σ

Notes: Employment growth rates are measured over two years conditional on survival. Own Improvement - Average is the employment growth rate after establishments improving their existing products subtracted with the average employment growth rate among survived establishments, and other relative rates are defined similarly. All observations are weighted by the employment-adjusted cross-sectional weights.

product improvements, regress Equation (1.8) for $j = \xi$, and use the estimate to calibrate ϵ_{own}. For a similar reason, I use the food & beverage sector to calibrate the elasticity of product expansion, ϵ_{exp}. The estimate for product expansion in the food & beverage sector is around 0.38, which gives $\epsilon_{exp} = 0.62$. In the case of own-product improvements from the consumer goods sector, the estimate is around 0.25. Thus, I set ϵ_{own} to 0.33.

The moments in Table 1.3 are matched after solving the equilibrium and simulating a panel survey in a way consistent with the German survey[17]. The model is exactly identified with six moments to match with six parameters. Overall, the model can match the moments exactly, despite the uncertainty associated with Monte Carlo simulations.

The step size of an own-product improvement λ targets the output growth rate on the BGP. Cost shifters of own-product improvements (c_{own}) and product expansion (c_{exp}) match the fraction of establishments that experience innovation events in the survey.

The probabilities of successful innovation conditional on positive survey answers, q_{own}

17. I first simulate 30 years of 1,000 establishments in each entering cohort. Then, I construct the three-year panel in a way consistent with the survey.

and q_{exp}, are to target how establishments grow after the own-product improvement and product expansion events in the survey. Intuitively, for other fixed parameters, if q_{own} and q_{exp} are larger then survey answers are translated into larger increases in employment size for establishments with positive survey answers. I match the difference in $EmpGr^{2+} - EmpGr^{1-}$, which is defined in Section 1.3.1, between average establishments and establishments that experience own-product improvements and product expansion.

The small additional size growth after product expansion already predicts a low value for q_{exp}. Assume no exit and no entry for simplicity. Then, on average, continuing establishments' growth rate is close to zero on the BGP. If an establishment with one product line experiences successful product expansion, the establishment growth rate must be about 100%. If an establishment with two product lines experiences successful product expansion on one of its product lines, the size growth rate must be 50%. Product-expanding establishments grow only about 1.3 percentage points faster than the average establishment. This small difference implies that product expansion answers in the survey are associated with a small number of additional product lines, causing a limited amount of product-line reallocation for productivity growth.

Lastly, the elasticity of substitution across product lines, σ, is calibrated to match the difference in $EmpGr^{1+} - EmpGr^{1-}$ between the average establishment and establishments that do not innovate in years t and $t+1$. If σ is higher, non-innovating establishments shrink at a higher rate because of continuous substitution towards better-quality intermediate goods.

Table 1.4 shows the values of calibrated parameters. The step size of an own-product improvement is calibrated to be 2% of the average quality. This is slightly bigger than the step size of product expansion in [1], 1.3%, but smaller than the average step size of

Table 1.4: Values of Calibrated Parameters

	Parameter	Value
λ	Step Size of Own-Product Improvement (%)	2.0
σ	Elasticity of Substitution across Products	1.7
c_{own}	Own-Product Improvement Cost Shifter	82301
c_{exp}	Product Expansion Cost Shifter	3889
q_{exp}	Probability of Successful Expansion (%)	3.9
q_{own}	Probability of Successful Improvement (%)	86

innovation in [24], 7.5%, and the step size of internal innovation in [5], 5.1%.

The elasticity of substitution across product lines is calibrated at 1.7, which implies that the quality of a product line depreciates by about 1% per year without innovation. This value is smaller than in what was assumed in [24], 4. While the average job destruction rate is 4.5% in a given year, non-innovating establishments in the data shrink at only a 2.3 percentage points higher rate than the average establishment. This difference implies that most job destruction happens regardless of technological obsolescence.

For both types of innovations, the cost shifters are large. These cost shifters are needed to replicate more than half of the establishments not involved in innovation in a given year. Own-product improvements have cost shifters larger than product expansion. A positive answer to the product expansion question is associated with only 0.04 additional product lines, but the success probability of an own-product improvement is 84%. Thus, the cost shifter of own-product improvements is larger to replicate the intensity of own-product improvements only 20 percentage points higher than the intensity of product expansion.

1.4 Quantitative Results

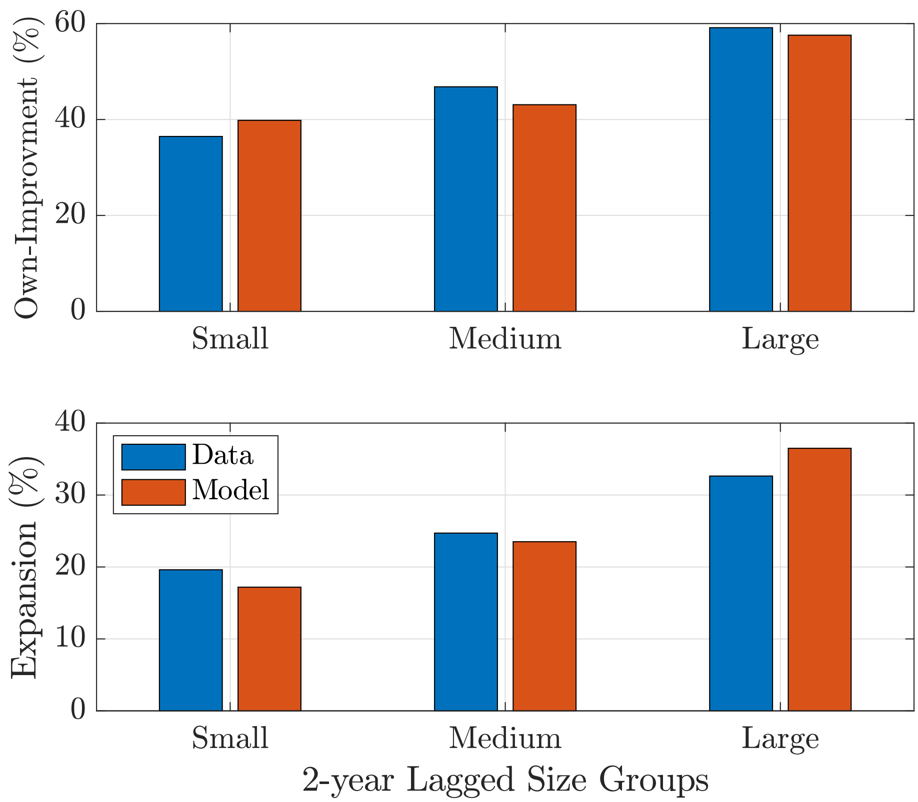
1.4.1 Model Fit

Figure 1.2 depicts the model-generated fractions of innovating establishments across different size groups. As in Section 1.3.1, larger establishments are more likely to innovate both in terms of own-product improvements and product expansion. This size dependency is consistent with the model. First, especially large establishments that hold more than one product line are mechanically more likely to experience an innovation event on one of their product lines because innovation events are independent across product lines. Second, in the model, more productive establishments are more incentivized to expand to another product line because they are also more productive on a new product line. Because of higher future returns to product expansion and low risk of being replaced with a new establishment, more productive establishments also tend to put more resources into own-product improvements. Establishment size is a noisy proxy for the underlying productivity of the establishment. Therefore, the size dependency of innovation frequencies in the data is replicated by the model, making more productive firms have stronger incentives to innovate.

Figure 1.3 shows the unconditional relative employment growth rates over $n = -3, \ldots, 3$ before and after innovation events. As discussed in Section 1.3.1, the establishments have pre-trends before their innovation events in time 0 in the data. The model replicates a part of these pre-trends by the selection of productive establishments for innovation. Establishments with innovation events in year 0 are more likely to be hit by other innovation shocks before the innovation year and have higher productivity levels than the average one.

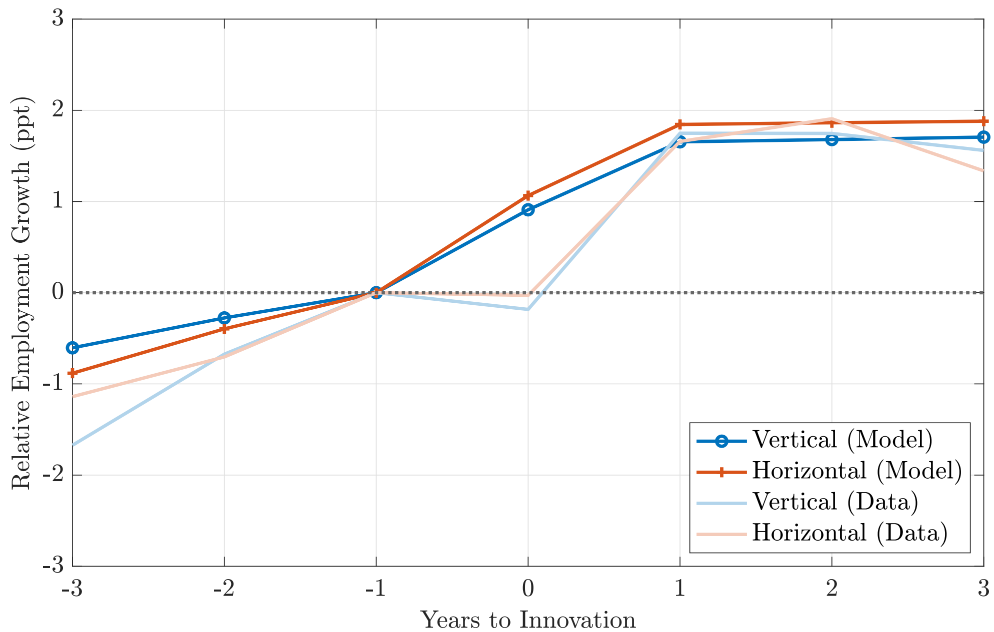
Figure 1.4 compares the model-generated job creation and destruction rates to the data counterparts. The model replicates only about 20% of labor reallocation rates in the data.

Figure 1.2: Innovation Intensities across Size Groups - Model vs. Data



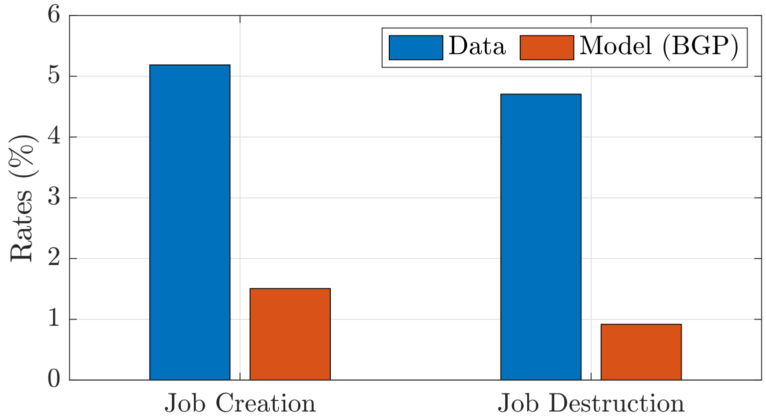
Notes: Innovation intensity is the fraction of workers in establishments with positive answers to the survey questions. Small, Medium, and Large are the first, the second, and the third tertile groups of the lagged employment size two years before the survey. All samples are weighted by their lagged employment size and sampling weights. Samples are pooled across different years.

Figure 1.3: Relative Employment Growth- Model vs. Data



Notes: Y-axis is the cumulative employment growth rates from year 0 calculated among establishments innovating in a given year (0) relative to the average establishment surviving in the data. The relative growth rate is normalized to be 0 in the previous year of the survey.

Figure 1.4: Job Creation and Destruction Rates



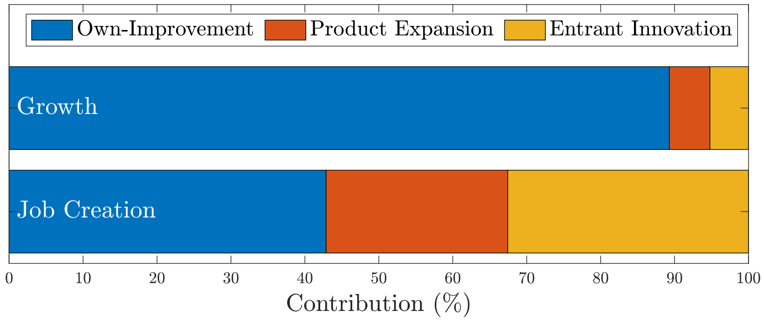
Notes: All rates are annual and calculated with samples younger than 30 years. Model-generated rates are calculated using simulated panels.

Most quantitative studies that do not measure innovation activities directly in the data, such as [39] and [24], assume in their calibration and estimation that all cross-sectional variances of employment, revenue, or productivity changes result from idiosyncratic innovation processes. The small magnitude of labor reallocation rates implied by the model suggests that most labor reallocation in the data is independent of innovation and such calibration and estimation strategies can make misleading results.

1.4.2 Balanced Growth Path Decomposition

Figure 1.5 shows the contribution of different types of innovation to aggregate growth and labor reallocation. See Equation (1.9) for the growth decomposition and Equation (1.7) for the job creation decomposition. Own-product improvements account for 90% of productivity growth on the BGP. This is because entrants and product-expanding incumbents generate small labor reallocation toward them. For product expansion and entrant innovation, large-scale job creation is needed for establishments with innovation events to replace existing establishments and contribute to productivity growth. Such replacements are not needed

Figure 1.5: Growth and Job Creation Decomposition on the BGP



Notes: Growth decomposition is derived in Equation (1.9) in Appendix 1.A.5. Job creation decomposition is derived in Equation (1.7).

for own-product improvements. As a result, even a small amount of labor reallocation can generate sufficient productivity growth when the growth is made by own-product improvements. Product expansion and entrant innovation make up only 5% of total productivity growth each.

On the other hand, own-product improvements account for only 43% of job creation. This is because own-product improvements do not replace workers within establishments but only add more workers on top of existing product lines. Conversely, relative to its contribution, product expansion generates more job creation in the economy with worker replacements across establishments. Entrant innovation also creates more jobs relative to its contribution to growth. This result is consistent with [23] and [26] that empirically find a disproportionately large contribution of start-ups on fluctuations of employment and new hires.

1.5 Application: 2020 R&D Tax Incentives

I apply the calibrated model to quantify the impact of an R&D tax incentive program[18]. This exercise is in line with [7] who use a quantitative endogenous growth model to evaluate the effect of R&D policies on aggregate productivity growth and welfare. I focus on the new R&D tax incentive policy that started in Germany in 2020. According to the OECD R&D Tax Incentive Indicators, the implied R&D tax subsidy rate jumped from -2% to 19% between 2019 and 2020 in Germany[19]. I model this as a 21 percentage points increase in the R&D subsidy rate.

I set the baseline BGP with zero subsidy rates on R&D expenditures. Then, the new R&D tax incentives are modeled as a positive 21% subsidy on incumbents' R&D expenditures on own-product improvements and product expansion. Thus, the new R&D costs to the individual establishments become $0.79 \times W_t c_{own}(\xi)$ and $0.79 \times W_t c_{exp}(\zeta)$ for own-product improvements and product expansion, respectively. I set these R&D subsidies financed by a lump-sum tax on the representative households. However, the labor market clearing condition remains the same as before. Labor demand takes the full R&D labor $c_{own}(\xi) + c_{exp}(\zeta)$ to determine the wage level.

I compare the new BGP with the R&D tax incentive to the baseline BGP. Then, I evaluate changes in aggregate moments over the transition path. I start from the baseline BGP, introduce an unexpected R&D subsidy rate change at $t = 0$, and compute the deterministic transition path to the new BGP with the R&D incentive. The equations used to calculate

18. See Online Appendix 1.D for another application exercise inspired by the Hartz Reform, a major labor market that happened in Germany during the mid-2000s.

19. This tax subsidy rate is defined as one minus B index, where B index is *'a measure of the level of pre-tax profit a "representative" company needs to generate to break even on a marginal, unitary outlay on R&D'*, OECD Measuring Tax Support for R&D and Innovation: Measurement (`https://www.oecd.org/sti/rd-tax-definition-and-measurement.htm`).

the transition path equilibrium are described in Online Appendix 1.C.1.

With a single aggregate labor supply and an entry rate on the BGP, the Frisch elasticity of labor supply η and entry elasticity ϵ_{entry} are not identified. In the baseline case, I set $\eta = 1$ and $\epsilon_{entry} = 0.1$. In Appendix 1.C.2, I also test various values for η and ϵ_{entry}. Higher labor supply elasticity implies a larger impact from R&D subsidy. On the other hand, despite alternative entry elasticity values, the results remain quantitatively similar because the entrant innovation does not contribute much to aggregate growth.

1.5.1 Balanced Growth Path

Table 1.5 compares the BGP moments before and after the new R&D tax incentive. The first column summarizes the baseline BGP while the fourth column summarizes the BGP after the R&D tax incentives. To distinguish the effect of R&D incentives through own-product improvements from the effect through product expansion, the second column summarizes the BGP that subsidizes only own-product improvements. Similarly, the third column indicates the BGP that subsidizes only product expansion.

Subsidizing own-product improvements is more important in accelerating productivity growth than subsidizing product expansion across different BGPs. This is because own-product improvements constitute the majority of productivity growth. Although the elasticity of product expansion is larger than the elasticity of own-product improvement, product expansion makes up only 5% of productivity growth. Thus, its role stays limited on the new BGP. Having universal subsidies for all types of incumbent innovation increases the productivity growth rate on the BGP by 0.1 percentage points per year. Due to more demand for R&D activities, the wage is higher by 3%. Entry value increases, but the increase in wage

Table 1.5: Balanced Growth Path Moments before and after R&D Incentives

Moment	Baseline	Own Subsidy	Expansion Subsidy	Full Subsidy
Output Growth Rate (%)	1.38	1.46	1.40	1.48
Wage	1.000	1.014	1.016	1.030
Own-Product Improvement Rate (%)	45.2	48.3	45.6	48.6
Product Expansion Rate (%)	0.85	0.84	0.96	0.95
Entry Rate (%)	1.20	1.20	1.20	1.20
Job Creation Rate (%)	1.51	1.51	1.76	1.73
Job Destruction Rate (%)	0.92	0.93	1.05	1.06

Notes: All rates are annual. Column Own Subsidy indicates the transition path that subsidizes only own-product improvements.

cancels out the increase in entry value. As a result, the entry rate stays almost the same across all BGPs.

Labor reallocation rates increase by more when product expansion is subsidized. When only own-product improvements are subsidized, annual job creation rates change by less than 0.01 percentage points despite the 0.08 percentage point increase in the productivity growth rate. On the other hand, when only product expansion is subsidized, the change in job creation rate is 0.25 percentage points even with the 0.02% increase in annual growth rate on the new BGP. Job destruction rates also increase more with the expansion subsidy than with the own-product improvement subsidy. Overall, because of low product expansion rates in the baseline BGP, changes in job creation and destruction rates are minimal.

1.5.2 Transition Path

Table 1.6 describes output responses and welfare effects of the R&D tax incentives over the transition path. In all cases, the output jumps down initially because more labor inputs are used for R&D and less for production. The own-product improvement subsidy and

Table 1.6: Effect of the R&D Incentives over the Transition Path

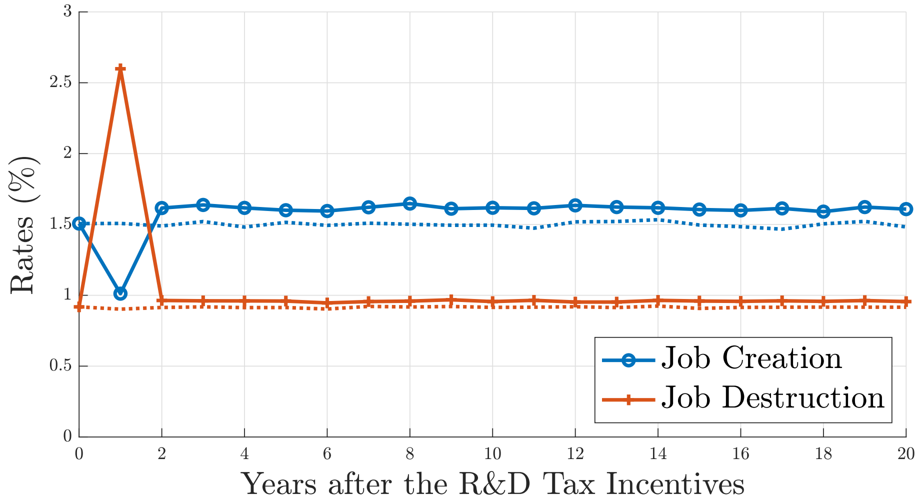
Moment	Own Subsidy	Expansion Subsidy	Full Subsidy
Initial Output Change (%)	-1.34	-1.28	-2.68
Catch-up Point (years)	16.7	45.0	24.6
Consumption Equivalent Variation (%)	2.50	-0.44	1.99
Own-Product Improvement (%)	2.47	0.22	2.74
Product Expansion (%)	-0.03	0.54	0.49
Entrant Innovation (%)	-0.01	0.15	0.14

Notes: All numbers in percent. Column Own Subsidy indicates the transition path that subsidizes only own-product improvements. The Consumption Equivalent Variation is a permanent increase in consumption for the representative household in the baseline economy to have the same lifetime utility as in the transition economy. Own-Product Improvement, Product Expansion, and Entrant Innovation are the contributions of each innovation type to welfare change. The rest of welfare change comes from changes in labor supply over the transition path. For the derivations, see Online Appendix 1.C.1.

the expansion subsidy cause similar initial output drops. However, the transition path under the expansion subsidy takes 45 years to catch up with the pre-incentive BGP, whereas the economy subsidizing own-product improvements exceeds the pre-incentive BGP after 17 years. Consistent with the BGP comparison in Section 1.5.1, product expansion only absorbs production labor without having sizeable growth effects. In the case of full R&D tax incentives, the initial output decrease is larger, but the economy catches up with the baseline BGP after 25 years.

Figure 1.6 describes job creation and destruction rates over the transition path (solid lines) and the baseline BGP (dotted lines). Because of a sharp increase in wage at $t = 0$, all establishments reduce their production labor demand. In the first year following the introduction of R&D incentives, this raises job destruction rates for non-innovating establishments and reduces job creation rates for innovating establishments. After the first

Figure 1.6: Job Creation and Destruction Rates over the Transition Path



Notes: All rates are annual and calculated from simulated panels younger than 30 years old over the transition path.

year, however, the wage level quickly converges to the new BGP level, and the levels of job creation and destruction rates become higher but close to the previous levels. As in the BGP case, the economy experiences small changes in labor reallocation rates because product expansion rates barely change in response to the subsidy.

The second panel of Table 1.6 summarizes welfare responses to the subsidies and the contribution of each innovation margin. Overall, the R&D incentive is welfare-improving. It is equivalent to a 2% permanent increase in the consumption of the representative household on the baseline BGP. Both own-product improvements and product expansion contribute to a welfare gain, but own-product improvements are quantitatively more important, making 81% (2.74/(2.74 + 0.49 + 0.14)) of dynamics gains from faster economic growth after the R&D incentives. With the incentives favoring only own-product improvements, the welfare gains are larger than the full incentive case.

On the other hand, for the product expansion incentives, the welfare effects are negative. The negative welfare impact of subsidizing product expansion comes from its stronger business stealing effect, as emphasized in [6]. Both own-product improvements and product expansion have positive externalities because future innovation is built on top of the current frontier knowledge of product lines, but its effect is ignored by firms deciding on innovation currently. At the same time, innovations have negative externalities from two kinds of business stealing. First, the relative quality of a product line depreciates if others innovate. Second, especially for product expansion and entrant innovation, innovation causes the creative destruction of existing producers on product lines. Thus, product expansion has larger negative externalities, and households are worse off under product expansion subsidies.

1.6 Concluding Remarks

In this paper, I use survey-based measures of establishment-level innovation activities and relate the measures to output growth and labor reallocation in the general equilibrium. This measure covers representative samples of establishments in Germany and captures knowledge creation and adoption activities in broad sectors, such as manufacturing, consumer service, and retail sectors. Moreover, the survey-based measures make it possible to distinguish own-product improvements and product expansion by self-reporting.

I construct a quantitative model where incumbents' innovation choices generate endogenous productivity growth and calibrate model parameters by matching moments from the innovation measures merged with an administrative data set on establishment-level employment. The calibrated model is then used to quantify the macroeconomic effects of a recent R&D tax incentive in Germany. The model predicts that the welfare of the overall German economy improves with more R&D investments. Welfare increases by 2%, where own-product improvements explain 81% of the gains from productivity growth. Because of the weak response of product expansion to the incentives, despite the growth responses through own-product improvements, labor reallocation rates barely change across BGPs and over transition paths.

The survey-based innovation measures open the possibility for further research. After merging the innovation survey data with the administrative employer-employee matched data, we can study how worker composition within establishments interacts with innovation decisions of establishments and how innovation events at the establishments affect the wage and job dynamics of workers. The new measure can supplement the patent-based measure of innovation in many ways.

1.A Model Appendix

1.A.1 Representative Household

The household block follows a standard setting in the Schumpeterian growth model literature as in [1]. The representative household gathers all the profits of firms and labor incomes together to determine a consumption path, given the sequences of wage $\{W_t\}_{t\geq 0}$ and real interest rates $\{r_t\}_{t\geq 0}$. The representative household maximizes the following lifetime utility:

$$\max_{C_t} \int_0^\infty e^{-\rho t} \left(\log(C_t) - \frac{\phi L_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}} \right) dt$$

subject to

$$C_t + \dot{b}_t = W_t L_t + \int_0^1 \pi_{jt} dj + r_t b_t$$

where the right-hand side is the total income of the household and b_t is the real bond holding with zero net supply. The income of the household is the sum of all the labor earnings ($W_t L_t$), the profits net of innovation costs (π_{jt}), and the interest rate of real bond holdings. In equilibrium, $C_t = Y_t$.

The Euler equation of the lifetime utility maximization is as follows:

$$\frac{\dot{C}_t}{C_t} = r_t - \rho.$$

On the balanced growth path where $C_t = Y_t$ grows at g_Y, the interest rate is simply

$$r_t = r = \rho + g_Y.$$

Next, the first-order condition with respect to labor supply gives a labor supply curve.

$$\phi \left(L_t^s\right)^{\frac{1}{\eta}} = \frac{W_t}{C_t} = w$$

Again, $w := W_t / Y_t$ is constant in the BGP equilibrium.

1.A.2 Derivation of the Value Function

The entire firm value is characterized by the following equation:

$$
\begin{aligned}
(r+\delta)\,\mathfrak{V}\left(\{x_j\}_{j=1}^{N_i}, W_t, Y_t\right) = \max_{\{\xi_j,\zeta_j\}\geq 0} \Bigg\{ & \sum_{j=1}^{N_i} Y_t\pi(x_j) - \sum_{j=1}^{N_i} g_x x_j \mathfrak{V}_{x_j}\left(\{x_{j'}\}_{j'=1}^{N_i}, W_t, Y_t\right) \\
& + g_Y Y_t \mathfrak{V}_{Y_t}\left(\{x_{j'}\}_{j'=1}^{N_i}, W_t, Y_t\right) + g_W W_t \mathfrak{V}_{W_t}\left(\{x_{j'}\}_{j'=1}^{N_i}, W_t, Y_t\right) \\
& - W_t \sum_j c_{own}(\xi_j) + \sum_j \xi_j \left(\mathfrak{V}\left(\{x_{j'}\}_{j'\neq j} \cup \{x_j+\lambda\}, W_t, Y_t\right) - \mathfrak{V}\left(\{x_{j'}\}_{j'=1}^{N_i}, W_t, Y_t\right)\right) \\
& - W_t \sum_j c_{exp}(\zeta_j) + \sum_j \zeta_j \left(p + (1-p)\,F(x_j)\right) \\
& \times \left(\mathfrak{V}\left(\{x_{j'}\}_{j'=1}^{N_i} \cup \{x_{N_i+1} = x_j\}, W_t, Y_t\right) - \mathfrak{V}\left(\{x_{j'}\}_{j'=1}^{N_i}, W_t, Y_t\right)\right) \\
& + \sum_j \tau(x_j)\left(\mathfrak{V}\left(\{x_{j'}\}_{j'=1}^{N_i} \setminus \{x_j\}, W_t, Y_t\right) - \mathfrak{V}\left(\{x_{j'}\}_{j'=1}^{N_i}, W_t, Y_t\right) - \kappa\right) - W_t\delta\kappa\#\left(\{x_j\}_{j=1}^{N_i}\right) \Bigg\}
\end{aligned}
$$

where $\mathfrak{V}_{x_j}(\left\{x_{j'}\right\}_{j'=1}^{N_i}, W_t, Y_t) = d\mathfrak{V}(\left\{x_{j'}\right\}_{j'=1}^{N_i}, W_t, Y_t)/dx_j$. Likewise, $\mathfrak{V}_X$ is the partial derivative of $\mathfrak{V}$ with respect to the variable in the subscript, X. I also use this notation of partial derivatives below.

First, guess and verify that $\mathfrak{V}\left(\{x_j\}_{j=1}^{N_i}, W_t, Y_t\right) = \sum_{j=1}^{N_i} V\left(x_j, W_t, Y_t\right)$, where

$$
\begin{aligned}
(r+\delta+\tau(x))\,V(x, W_t, Y_t) = \max_{\xi,\zeta\geq 0} \Bigg\{ & Y_t\pi(x) - g_x x V_x(x, W_t, Y_t) \\
& + g_Y Y_t V_{Y_t}(x, W_t, Y_t) + g_W W_t V_{W_t}(x, W_t, Y_t) \\
& - W_t c_{own}(\xi) + \xi\Big(V(x+\lambda, W_t, Y_t) - V(x, W_t, Y_t)\Big) \\
& - W_t c_{exp}(\zeta) + \zeta\left(p + (1-p)F(x)\right) V(x, W_t, Y_t) \\
& - (\tau(x)+\delta)\,\kappa W_t x \Bigg\}
\end{aligned}
$$

Next, guess and verify that $V_t(x, Y_t, W_t) = Y_t v(x)$, where

$$
\begin{aligned}
(\rho + \delta + \tau(x))\, v(x) = \max_{\xi, \zeta \geq 0} \Bigg\{ & \pi(x) - g_x x v'(x) \\
& - w c_{own}(\xi) + \xi \Big(v(x+\lambda) - v(x) \Big) \\
& - w c_{exp}(\zeta) + \zeta \left(p + (1-p) F(x)\right) v(x) \\
& - (\tau(x) + \delta)\, \kappa w x \Bigg\}
\end{aligned}
$$

Use $\rho = r - g_Y$, $V_W(x, W_t, Y_t) = 0$ and $w = W_t/Y_t$.

1.A.3 Step Size in the Quality Space

I show that there exists an innovation step size function, $\lambda(a, A)$, in the absolute quality space $a \in \mathcal{A}$, so that the step sizes in the relative quality space $x \in \mathcal{X}$ are constant at λ.

$$
\begin{aligned}
x + \lambda &= \frac{(a + \lambda(a, P))^{\sigma}}{A^{\sigma - 1}} \\
\left(x A^{\sigma-1} + \lambda A^{\sigma-1}\right)^{1/\sigma} &= \left(a^{\sigma} + \lambda A^{\sigma-1}\right)^{1/\sigma} \\
&= a + \lambda(a, A) \\
\& = 1
\end{aligned}
$$

Thus, for any $\lambda > 0$, $\lambda(a, A) := \left(a^{\sigma} + \lambda A^{\sigma-1}\right)^{1/\sigma} - a$ ensures the constant step size in the relative quality space.

1.A.4 Derivation of the Distribution Equation and the Growth Rate

The proof follows [1] who use discrete-time approximation to derive the distribution equation. The discrete-time analog of the distribution equation is given by the following equation.

$$
\begin{aligned}
F(x) \approx\ & F(x + \Delta g_x x) - \Delta\delta F(x + \Delta g_x x) \\
& - \int_{s \in (x-\lambda, x]} \Delta\xi(s) dF(s) \\
& - (1-p) \left(\int_{s > x} \Delta\zeta(s) dF(s) + \Delta\chi \int_{s > x-\lambda} dF(s) \right) F(s) \\
& + p \left(\int_{s \leq x} \Delta\zeta(s) dF(s) + \int_{s \leq x-\lambda} \Delta\chi dF(s) \right)
\end{aligned}
$$

Divide both sides by Δ, and let $\Delta \to 0$.

1.A.5 Equation of the Growth Rate

$$
\begin{aligned}
g_Y(\sigma-1) = g_x = & \underbrace{\int \left[\int_{s\in(x-\lambda,x]} \xi(s) dF(s) \right] dx}_{\text{own-product improvement}} \\
& + p \underbrace{\int \left[\int_{s>x} \zeta(s) dF(s) \right] dx - p\bar{\zeta}}_{\text{product expansion (1)}} \\
& + p \underbrace{\int \left[\chi \int_{s>x-\lambda} dF(s) \right] dx - p\chi}_{\text{entrant innovation (1)}} \\
& + (1-p) \underbrace{\int \left(\int_{s>x} \zeta(s) dF(s) \right) F(x) dx}_{\text{product expansion (2)}} \\
& + (1-p) \underbrace{\int \left(\chi \int_{s>x-\lambda} dF(s) \right) F(x) dx}_{\text{entrant innovation (2)}}
\end{aligned}
\tag{1.9}
$$

In this equation, $\bar{\zeta} := \int \zeta(x)(p + (1-p)F(x))dF(x)$ is the share of product-expanding lines for a unit amount of time.

1.B Data Appendix

1.B.1 Innovation Measures

The IAB-BP asks its respondents whether they had the following four types of innovation activities in the previous year of the survey. Two of the questions are used as a measure of own-product improvements, and one of them is used as a measure of product expansion. The other question is not used in the paper but enters as a control in the regression equation in 1.B.3.

1. **Quality Improvement**: In the last business year, did your establishment improve or further develop a product or service which had previously been part of your portfolio? ($\in$ own-product improvement in the paper)

2. **Process Innovation**: Did you develop or implement procedures in the last business year which have noticeably improved production processes or services? ($\in$ own-product improvement in the paper)

3. **Product Expansion**: In the last business year, did your establishment start to offer a product/service that had been available on the market before? (= product expansion in the paper)

4. **Variety Creation**: Have you started to offer a completely new product or service in the last year for which a new market had to be created? (excluded from the paper)

Table 1.7 shows the frequencies of innovation separately for the four questions across different size groups with equal numbers of workers. Each observation consists of an establishment in a given year, and all samples are pooled over different years. Consistent with the paper, I weight samples with 2-year lagged employment size from the survey year multiplied by cross-sectional weights from the data provider in calculating innovation intensity. Quality improvements, which are included as a type of own-product improvements along with process innovation, are the most common type of innovation in the survey, followed by product expansion and process innovation. Variety creation is the least common form of innovation in the survey, and variety creation is not correlated significantly with innovating establishments' growth. As a result, the variety creation measure is excluded from the analysis in the paper. For all types of innovation, larger establishments are more likely to innovate.

Table 1.7: Raw Innovation Intensity across Size (in %)

	Quality Improv.	Product Expansion	New Variety	Process Innov.	Any Innov.	N. Est.
All	44.57	25.49	10.68	21.67	52.63	49,411
Small	34.13	19.61	6.62	13.23	42.16	29,886
Medium	43.93	24.71	9.97	20.64	52.68	12,596
Large	56.47	32.64	15.79	31.83	63.86	6,929

Table 1.8 shows the innovation frequencies across establishment age groups with equal numbers of workers. Old establishments are almost as likely as young establishments to participate in all innovation activities despite a positive correlation between employment size and age. This contrasts with previous studies using patent measures, such as [1] who emphasize higher intensities of young establishments to innovate.

Table 1.8: Innovation Frequencies across Age (in %)

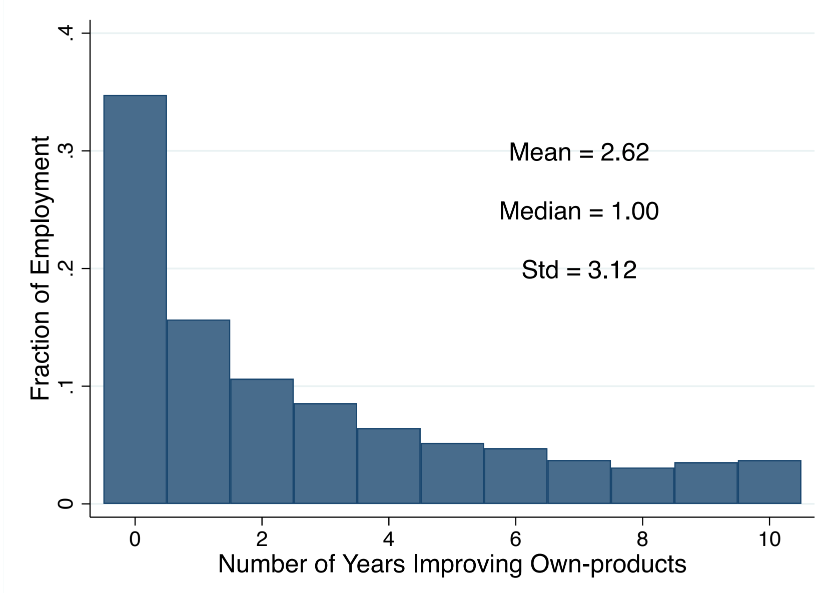
	Quality Improv.	Product Expansion	Variety Creation	Process Innov.	Any Innov.	N. Est.
All	44.57	25.49	10.68	21.67	52.63	49,411
Young	44.31	26.35	9.81	21.37	52.95	18,054
Medium	45.68	25.71	11.18	22.02	52.99	18,735
Old	43.55	24.15	11.18	21.64	51.78	12,622

In all empirical exercises (including the two tables above), I pool all the establishment samples across different years. As a result, one establishment appears in the data set multiple times over different years. To gain insight into how an establishment innovates over time in the data, Figures 1.7 and 1.8 display the distribution of the numbers of years improving own products and expanding to new product varieties for each establishment, respectively[20].

20. To include as many establishments as possible, I weight each sample by the employment size of the

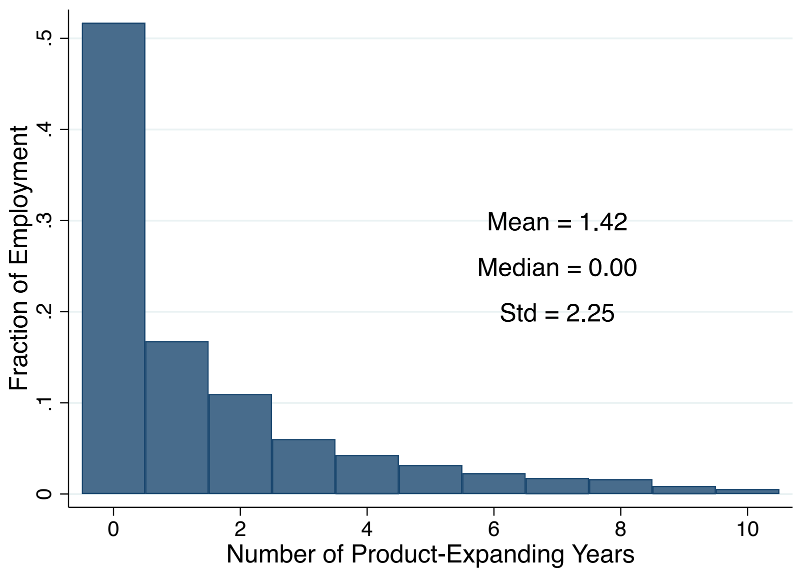
Since innovation questions appear in ten years of the survey, the maximum number of innovation years is ten. Innovation is concentrated around a small subset of establishments in the survey. Some establishments do not engage in innovation activities at all while a few establishments do innovate almost every year. Overall, the distribution for own-product improvements is placed to the right of the distribution for product expansion.

Figure 1.7: Number of Own-Product Improving Years Per Worker



survey year multiplied by the cross-sectional weights from the data provider, compared to the lagged employment size in the previous tables.

Figure 1.8: Number of Product-Expanding Years Per Worker



Because of this high heterogeneity across establishments in Figures 1.7 and 1.8, innovation in a given year predicts a higher probability of innovation in other years in Figures 1.9 and 1.10. First, both types of innovation have a positive auto-correlation. Own-product improvements and product expansion in year 0 predict higher probabilities of own-product improvements and product expansion in other considered years relative to the averages, indicated by the navy dashed lines for own-product improvements and the maroon dashed lines for product expansion. Second, own-product improvements and product expansion are positively correlated with each other. Own-product improvements in year 0 are associated with overall higher probabilities of product expansion in all considered periods, and vice versa. Lastly, the forward correlation is slightly smaller than the backward correlation; innovation in year t predicts a slightly higher probability of innovation before than after. This result is consistent with the fraction of innovating establishments marginally decreasing in establishment age in Table 1.8.

Figure 1.9: Innovation Intensities Conditional on Own-Product Improvement

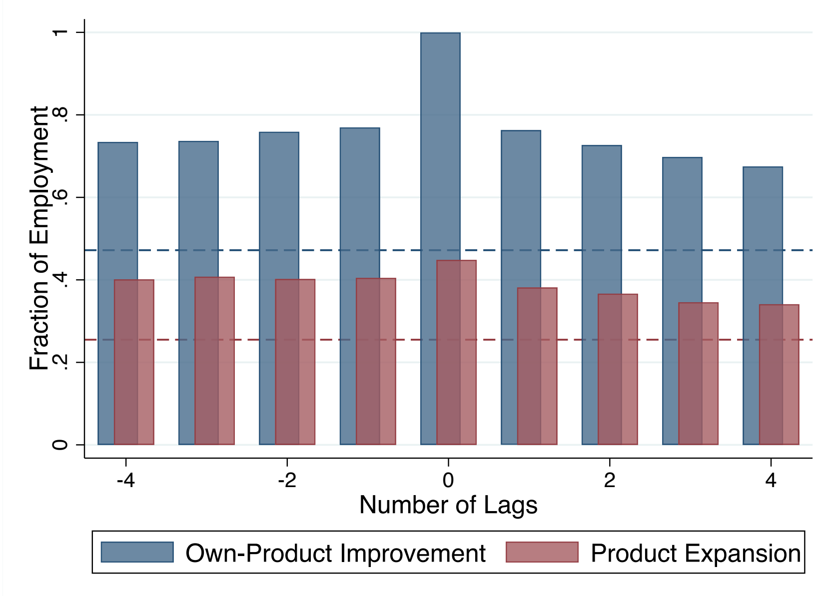
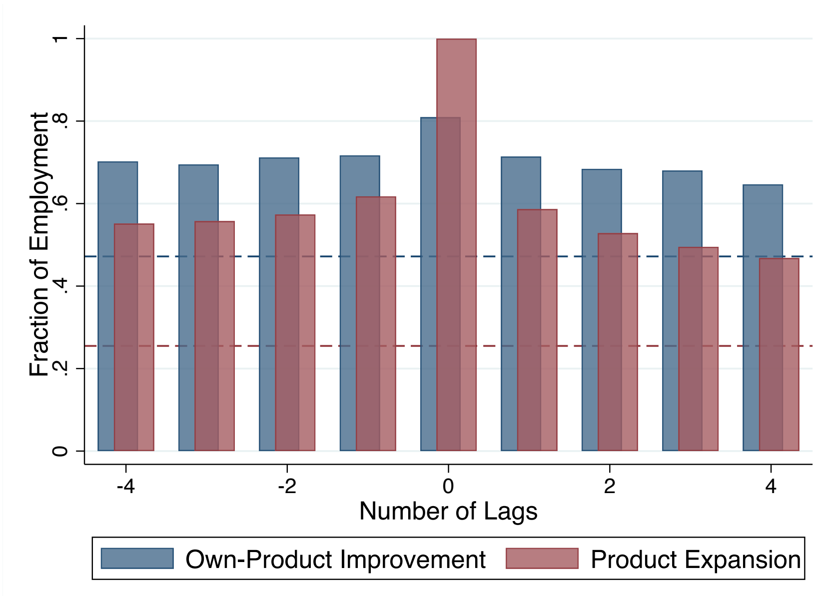


Figure 1.10: Innovation Intensities Conditional on Product Expansion



1.B.2 Comparison to Patent-Based Measures

I compare the survey-based measures of innovation to the patent-based measures, which have been widely used in innovation literature. Unfortunately, it is impossible to match patents to establishments in IAB-BP because of the anonymization. As a result, I match the class of patents to the sector of establishment and construct a sectoral panel. I then count the number of patents granted to German entities by the United States Patent and Trademark Office (USPTO) in each sector, using the raw patent data parsed and managed by `patentsview.org`. I first translate the cooperative patent class endowed by the USPTO to the 3-digit North America Industry Classification System (NAICS) Code of 2007 using probabilistic crosswalks constructed in [25]. I manually match the 3-digit NAICS code to the sectoral specification of IAB-BP.

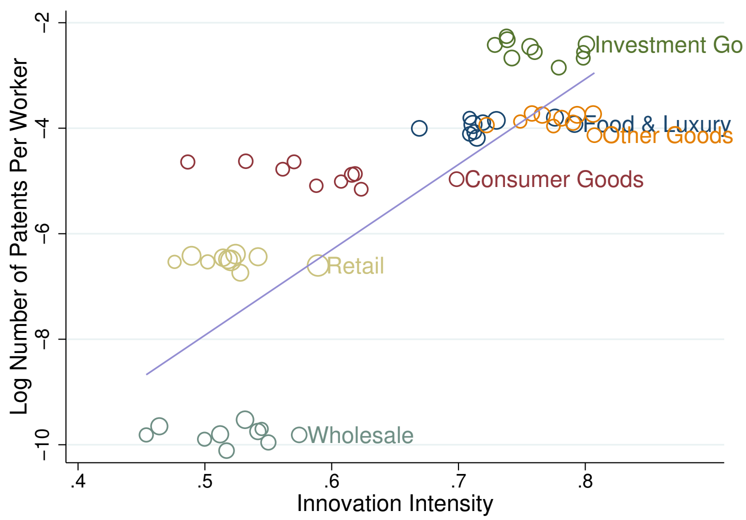
The patent-based measure of innovation does not exist for agriculture, mining, utility, or more importantly, service sectors. Patent measures exist primarily for manufacturing sectors where measuring new knowledge is more tangible whereas innovations made in the service sector are often hard to patent. Thus, I only compare the manufacturing sectors having both types of measures.

Then, I compare the average number of patents per worker with intensities of own-product improvements and product expansion in each year and sector[21]. In Figure 1.11, the fraction of innovating establishments in each sector and year is overall positively correlated with the number of patents per worker in that sector and year in the pooled sample, and the correlation coefficient is 0.81. This positive correlation, however, comes more from sectoral heterogeneities than time-series variations within each sector. Indeed, within each sector, the

21. To maximize the number of observations, I weight each establishment sample by year with the employment size of the survey year multiplied by the cross-sectional weights.

log number of patents per worker is almost flat over the fraction of innovating establishments. Incorporating sectoral heterogeneities is preferred in this case because there can be lags between the appearance of frontier knowledge, which is proxied by the patent data, and the adoption of new knowledge, which appears as the fraction of innovating establishments.

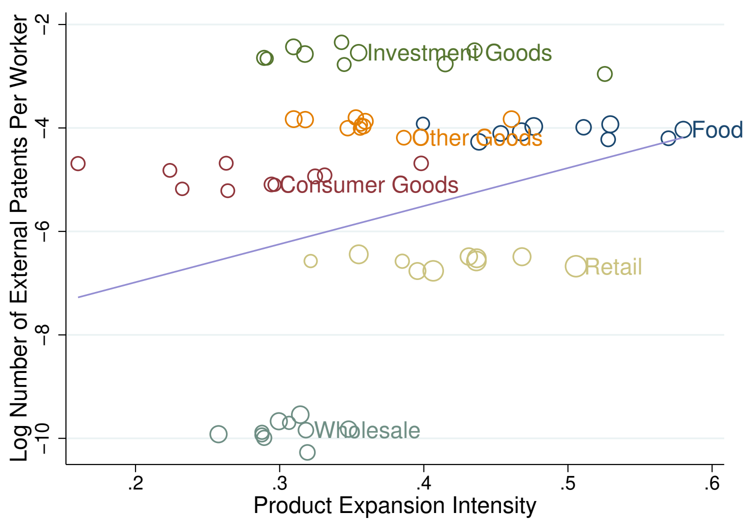
Figure 1.11: Innovation Intensity and the Number of Patents



In Figures 1.12 and 1.13, I distinguish between own-product improvements and product expansion in the survey measure. I also distinguish external and internal patents as in [5] wherein internal patents are defined as patents that cite other patents granted to their assignees for more than half of the total citations. External patents are all patents other than internal patents. [5] use internal versus external patents to measure innovation over firms' previous product lines versus innovation made over others' product lines. I classify patents using the previously written criterion and recalculate the number of internal and external patents in each sector and year. Then I draw scatter plots of the number of internal and external patents per worker against the fraction of establishments with own-product improvements and product expansion, respectively.

Figure 1.12: Own-Product Improvement Intensity and the Number of Internal Patents

Figure 1.13: Product Expansion Intensity and the Number of External Patents



Figures 1.12 and 1.13 show the results. In Figure 1.12, the intensity of own-product improvements at the sector by year level is still positively associated with the number of internal patents per worker, with a correlation coefficient of 0.72. Again, this positive correlation stems more from the sectoral heterogeneities in the average intensity of own-product

improvements and the number of internal patents than from within-sector variations. Meanwhile, in Figure 1.13, the intensity of product expansion is weakly correlated with the number of external patents per worker with a correlation coefficient of 0.22. For example, the retail sector has a relatively higher fraction of product-expanding establishments than other manufacturing sectors, but its number of external patents is lower than the investment goods sector. This contrasts with the own-product improvement case where the retail sector has both a lower intensity of own-product improvements than most manufacturing establishments and a lower number of internal patents per worker.

1.B.3 Surveyed Innovation and Establishment Performance

To investigate the implications of innovation measures at the establishment level more rigorously, I regress a statistical model of dynamic correlations of establishment-level behaviors with innovation dummies using the specification below. First, the dependent variables are defined in the following list. Growth rates are defined in a way similar to [17].

- Employment growth rate = $(AdmEmp - L.AdmEmp)/(\frac{1}{2}AdmEmp + \frac{1}{2}L.AdmEmp)$
- Wage, Revenue, and Investment growth rates are defined similarly
- Hire rate = $2 \times Hire/(\frac{1}{2}AdmEmp + \frac{1}{2}L.AdmEmp)$
- Separation rate = $2 \times Separation/(\frac{1}{2}AdmEmp + \frac{1}{2}L.AdmEmp)$
- Training rate = $2 \times \#ClassParticipants/(\frac{1}{2}AdmEmp + \frac{1}{2}L.AdmEmp)$
- Establishment age = survey year - the first year of appearance in the administrative data

where

- $AdmEmp$ = Employment of an establishment as of June 30 in the survey year from the administrative data
- $Hire$ = Total number of newly hired workers in the first half of the survey year from the survey
- $Separation$ = Total number of separated workers in the first half of the survey year from the survey
- $Wage$ = Imputed daily wage of full-time employees as of June 30 in the survey year from the administrative data
- $Revenue$ = Business volume in the previous year from the survey
- $Investment$ = Sum of investment expenditures in the previous year from the survey
- $\#ClassParticipants$ = The number of classes participants at least partially covered by the establishment from the survey

All samples are weighted by the product of two components: the cross-sectional weight provided by the IAB and the two-year moving average employment of the survey year in the administrative data. Since the administrative data starts in 1975, the ages of establishments that started before that year are unknown. As a result, I only include establishments younger than 30 years in 2008. For consistency over time, I only use establishments younger than 30 years in later years as well[22]. Table 1.9 shows the summary statistics for the dependent variables in the regression exercise. Each observation is weighted by the average employment between the current and the previous years.

22. Thus, if the establishment age exceeds 30 in the current year, it is included in the data in the previous year but not in the current year

Table 1.9: Summary Statistics - Outcome Variables (in %)

	Mean	Sd	Median	1st Q.	3rd Q.	N.
Employment Growth Rate	0.92	21.27	0.00	-4.65	7.06	81,286
Hire Rate	14.52	29.81	5.00	0.00	16.45	81,011
Separation Rate	12.12	26.64	4.65	0.00	13.11	81,074
Wage Growth Rate	2.12	10.02	1.90	-0.79	4.91	73,735
Revenue Growth Rate	2.96	25.29	1.81	-4.88	11.11	58,651
Investment Growth Rate	-3.39	135.25	0.00	-112.57	98.51	59,436
Training Rate	69.94	102.29	39.22	3.37	107.05	68,126

Employment-related variables imply that most establishments in the sample neither hire new workers nor separate from their existing workers. As a result, they stay at their initial employment size while the average establishment grows *conditional on survival.* Wage and revenue increase, but investment dwindles on average as the establishment ages. An average establishment has approximately 70% of workers trained, but a median firm has only 39% of its employees trained per year (at least at a partial expense of the establishment[23]). Finally, all the establishment-level variables have large cross-sectional dispersion.

The following regression specifications, similar to the event study specification, are used to estimate dynamic correlations of innovation dummies with dependent variables before and after the innovation events.

$$Y_{it} = \sum_{s=-5}^{5} \mathbf{1}^a_{it+s}\beta^a_s + \delta_i + \gamma_t + \varepsilon_{it} \tag{1.10}$$

Y_{it} is employment growth, hire, or separation rates of establishment i at year t. $\mathbf{1}^a_{it+s}$ is indicator of innovation type a, either own-product improvements (*own*) or product expansion

23. Since this question asks the number of class participants in the training program, it can be larger than the number of employees if some workers participate in the program for more than one time.

(exp). δ_i is the establishment fixed effect. γ_t is the year fixed effect.

In this regression, I use all samples from 2003—five years before the beginning of the innovation modules—to estimate the pre-trend. To maximize the number of observations, I include samples even if their innovation behaviors in some years are not known. Consequently, $\mathbf{1}^a_{it+s} = 0$ if the sample is not surveyed in year $t+s$, $s \neq 0$[24].

I define the baseline variable changes of the innovation year as the changes made between the innovation year and the year before. Since the survey asks about innovation activities in the previous year, while the wage expense and the employment variables are defined as of June of the survey year, the growth rate after the innovation may be the one between the innovation year and the previous year of the innovation. However, as shown in Section 3.1, most firms do not experience a size growth relative to an average firm between the innovation year and the previous year. Thus, I display the employment growth rate between the survey year and the previous year as the baseline growth rate of the innovation year if the innovation variable takes the value of one in the same survey. I set the same baseline year for other rates regarding hires, separations, investment growth, revenue growth, and employee training. The lagged terms in the regression equations are defined in the regression accordingly.

Similarly, because the numbers of hires and separations are defined over the first six months of the survey year, the hire and the separation rates of the year are defined as the rates of the innovation year if the innovation activities of the previous year took place in the survey of the current year. The survey asks about the profits and the investments in the previous year of the survey. Thus, the profits and the investments of the survey year are the profits and the investments of the innovation year if the innovation dummies are one in the survey of the current year. The lagged terms in the regression equations are defined in the

24. If the sample is not surveyed in t, its cross-sectional weight is zero, and the sample is excluded from the regression.

regression accordingly.

I further consider the following specification where I include all the innovation types surveyed in the data. This specification controls for any spurious correlation of individual innovation types to outcome variables Y_{it} through other types of innovation[25].

$$Y_{it} = \sum_{s=-5}^{5} \mathbf{1}_{it+s}^{own} \beta_s^{own} + \sum_{s=-5}^{5} \mathbf{1}_{it+s}^{exp} \beta_s^{exp} + \sum_{s=-5}^{5} \mathbf{1}_{it+s}^{newvar} \beta_s^{newvar} + \delta_i + \gamma_t + \varepsilon_{it} \tag{1.11}$$

$a = newvar$ indicates the creation of entirely new products, which is also reported in the survey.

Table 1.10 shows estimation results on employment-related variables. Own-product improvements predict an increase in employment growth by 2.5 percentage points in the innovation year, but the correlation becomes weaker three years after. On the other hand, product expansion correlates significantly with increases in employment in the innovation year. This correlation accumulates over time and becomes larger in three years (compare the third to the sixth columns), from 1.4 percentage points in the innovation year to 2.3 percentage points three years after.

Additional employment growth after the two innovation types entirely comes from additional hires. Hire rate results are consistent with employment growth results: own-product improvements are associated with a larger short-term but a smaller medium-term growth through more hires. Product expansion is associated with fewer short-term hires but with more medium-term hires. The coefficients of own-product improvements and product expansion on separation rates are overall insignificant and small in magnitude.

25. Samples with missing growth rates are excluded. These samples are often entrant and exiting establishments but also contain samples that disappeared or are added to the panel.

Table 1.10: Regression Results - Employment, Hires, and Separations

Dependent Variable: Employment Growth Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	3.00***		2.47***	2.04***		0.98
Improvement	(0.36)		(0.40)	(0.64)		(0.74)
Product		2.51***	1.39***		3.20***	2.28**
Expansion		(0.42)	(0.47)		(0.78)	(0.94)
N.	76,542	76,542	76,542	76,542	76,542	76,542
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Dependent Variable: Hire Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	2.57***		2.14***	1.80***		0.75
Improvement	(0.38)		(0.42)	(0.67)		(0.78)
Product		2.21***	1.62***		3.40***	3.01***
Expansion		(0.44)	(0.50)		(0.82)	(0.99)
N.	76,258	76,258	76,258	76,258	76,258	76,258
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Dependent Variable: Separation Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	0.67*		0.48	1.47**		0.77
Improvement	(0.36)		(0.39)	(0.63)		(0.73)
Product		0.36	-0.20		1.84**	0.52
Expansion		(0.41)	(0.47)		(0.77)	(0.93)
N.	76,312	76,312	76,312	76,312	76,312	76,312
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Notes: In the columns specified as 1 Year and 4 Years, estimates for β_0^a and $\sum_{s=0}^{3} \beta_s^a$ are reported, respectively. The third and the sixth columns follow regression equation (2), and all the other columns follow regression specification (1). Numbers in the parentheses are the standard errors of the estimates. $***$ - Significant at 1%, $**$ - Significant at 5%, $*$ - Significant at 10%.

These properties are consistent with the interpretation of innovation types in the structural model of endogenous innovation choice in Section 1.2. In the model, own-product improvements are associated with an increase in the quality of a product line by an establishment originally holding the line. This leads to a small increase in employment, and the effect disappears quickly as the quality depreciates over time. On the flip side, product expansion is modeled as an expansion of an establishment to a new product line. As a result, employment size increases more—and the effect lasts until the new product line is taken by another establishment. The accumulated effect of product expansion over the medium term can be explained by extending the model with learning or adjustment frictions.

In Tables 1.11 and 1.12, I show the regression results on additional variables such as wage, revenue, investment growth rates, and the fraction of trained employees. With large measurement errors associated with the surveyed outcome variables, the standard errors are large and coefficient estimates are overall insignificant. Both own-product improvements and product expansion are not associated with wage increases, as shown in the first panel. Own-product improvements are weakly correlated with a revenue increase in the innovation year but lead to decreases in revenue three years after. This, as in the case of employment, suggests that the increase in profitability after own-product improvements disappears quickly and the establishment eventually shrinks without further innovation. Product expansion is significantly associated with revenue increases, and the effect accumulates over time as in the employment growth. Both innovation types are associated with a large increase in investment, but own-product improvements have a quantitatively larger correlation with investment growth. Lastly, the fraction of trained employees increases after own-product improvements but not after product expansion. This result suggests that improving own products requires upskilling of workers.

Table 1.11: Regression Results - Wage and Revenue

Dependent Variable: Wage Growth Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	-0.31		-0.22	0.07		0.68*
Improvement	(0.20)		(0.22)	(0.35)		(0.40)
Product		0.10	0.41		0.14	0.67
Expansion		(0.23)	(0.26)		(0.42)	(0.51)
N.	69,412	69,412	69,412	69,412	69,412	69,412
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Dependent Variable: Revenue Growth Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	1.42***		0.91	-0.78		-1.33
Improvement	(0.53)		(0.58)	(0.93)		(1.07)
Product		1.90***	2.06***		0.96	2.80**
Expansion		(0.59)	(0.67)		(1.11)	(1.33)
N.	54,924	54,924	54,924	54,924	54,924	54,924
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Notes: In the columns specified as 1 Year and 4 Years, estimates for β_0^a and $\sum_{s=0}^{3} \beta_s^a$ are reported, respectively. The third and the sixth columns follow regression equation (2), and all the other columns follow regression specification (1). Numbers in the parentheses are the standard errors of the estimates. $***$ - Significant at 1%, $**$ - Significant at 5%, $*$ - Significant at 10%.

Table 1.12: Regression Results - Investment and Employee Training

Dependent Variable: Investment Growth Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	32.65***		28.05***	20.45***		13.32**
Improvement	(3.01)		(3.28)	(5.25)		(6.04)
Product		18.06***	8.78**		17.83***	8.42
Expansion		(3.36)	(3.78)		(6.33)	(7.55)
N.	55,103	55,103	55,103	55,103	55,103	55,103
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Dependent Variable: Fraction of Trained Employees

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	32.74***		33.35***	57.73***		60.58***
Improvement	(6.39)		(7.01)	(11.77)		(13.66)
Product		18.34**	2.78		24.49*	-12.98
Expansion		(7.30)	(8.37)		(14.32)	(17.34)
N.	62,196	62,196	62,196	62,196	62,196	62,196
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Notes: In the columns specified as 1 Year and 4 Year, estimates for β_0^a and $\sum_{s=0}^{3} \beta_s^a$ are reported, respectively. The third and the sixth columns follow regression equation (2), and all the other columns follow regression specification (1). Numbers in the parentheses are the standard errors of the estimates. $***$ - Significant at 1%, $**$ - Significant at 5%, $*$ - Significant at 10%.

1.B.4 Robustness Check: Integration of New Business Units

Product expansion of incumbent establishments does not necessarily mean an improvement of an existing product variety if the establishment may simply take on the new product without any change after mergers and acquisitions at the firm level. Moreover, employment growth after the integration of other business units may not reflect the labor reallocation process that increases productivity in the aggregate economy. If most of the business expansion activities in the survey result from this integration and this integration does not contribute to productivity growth[26], the calibrated model will overstate the contribution of product expansion on growth and labor reallocation, which is already small. In this section, I control for such business structure changes and show that the empirical results are robust.

I can distinguish establishments with firm-level organizational changes using the following questions.

1. Were parts of this establishment closed down or relocated with other company units between 1 July of the previous year and 30 June of the survey year, or were they separated and continued as independent businesses?

2. Conversely, were there any organizational developments that resulted in the integration of other establishments or establishment units into your company?

I use the second question to identify establishments with newly integrated units at the firm level and exclude them in the regression analysis in Appendix 1.B.3. Establishments are more likely to improve their own products (70%) and expand to new product varieties (46%) when their companies integrate new business units. However, only 1% of establishments, which account for 3.6% of employment in the entire sample, report that their companies integrated new business units. Larger establishments are more likely to fall into this category with 2.6% of establishments experiencing business integration in the largest employment size group compared to only 0.6% of establishments in the smallest group. Thus, the results do not change significantly by excluding these establishments.

26. Economic theories about mergers and acquisitions, such as [32], assume that mergers and acquisitions reallocate the capital from less efficient firms to more efficient firms, generating aggregate productivity gains. If mergers and acquisitions are a medium for firms and establishments to expand and innovate existing product varieties, then including integrated establishments is more desirable. Thus, I take this approach for the baseline.

Table 1.13: Regression Results - Robustness

Dependent Variable: Employment Growth Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	2.85***		2.41***	1.70***		0.68
Improvement	(0.37)		(0.40)	(0.65)		(0.75)
Product		2.08***	0.88*		2.68***	1.63*
Expansion		(0.42)	(0.48)		(0.79)	(0.95)
N.	72,443	72,443	72,443	72,443	72,443	72,443
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Dependent Variable: Hire Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	2.61***		2.27***	1.87***		0.96
Improvement	(0.39)		(0.43)	(0.69)		(0.80)
Product		1.98***	1.32***		3.20***	2.67***
Expansion		(0.45)	(0.51)		(0.85)	(1.01)
N.	72,174	72,174	72,174	72,174	72,174	72,174
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Dependent Variable: Separation Rates

	1 Year	1 Year	1 Year	4 Years	4 Years	4 Years
Own-product	0.63*		0.41	1.25*		0.53
Improvement	(0.37)		(0.40)	(0.65)		(0.76)
Product		0.44	-0.08		1.73**	0.50
Expansion		(0.42)	(0.48)		(0.80)	(0.96)
N.	72,226	72,226	72,226	72,226	72,226	72,226
Other Innov.			✓			✓
Fixed Effects	Est.	Est.	Est.	Est.	Est.	Est.

Notes: In the columns specified as 1 Year and 4 Year, estimates for β_0^a and $\sum_{s=0}^{3} \beta_s^a$ are reported, respectively. The third and the sixth columns follow regression equation (2), and all the other columns follow regression specification (1). Numbers in the parentheses are the standard errors of the estimates. $***$ - Significant at 1%, $**$ - Significant at 5%, $*$ - Significant at 10%.

Tables 1.13 show the results on employment-related variables with sub-samples of establishments that report no firm-level integration in the current year as well as in the previous year. For own-product improvements, the coefficient estimates on employment growth stay almost the same as in Table 1.10. On the other hand, for product expansion, the coefficient estimates on employment growth become 60-70% smaller and less significant, implying that the correlation is larger for establishments with a firm-level integration. Still, the effect remains positive even for establishments without firm-level integration. For hire rates, the changes in coefficients were smaller than for employment growth rates with significance remaining strong.

1.C Counterfactual Appendix

1.C.1 Transition Path: Details

I first fix Δ, the length of time interval, to approximate the continuous-time equations. The subscript t means the object evaluated at time t. Then, the value function along the transition path satisfies the following equation:

$$\begin{aligned}\left(\rho+\delta+\tau_{t+\Delta}\left(x\right)\right)v_{t}\left(x\right)=\pi\left(x\right)-g_{x,t+\Delta}xv_{t+\Delta}'\left(x\right)+\frac{v_{t+\Delta}(x)-v_{t}(x)}{\Delta}\\ -w_{t}c_{own}\left(\xi\left(x\right)\right)+\xi\left(x\right)\left(v_{t+\Delta}\left(x+\lambda\right)-v_{t+\Delta}\left(x\right)\right)\\ -w_{t}c_{exp}\left(\zeta\left(x\right)\right)+\zeta\left(x\right)\left(p_{t}+(1-p_{t})F_{t+\Delta}(x)\right)v_{t+\Delta}\left(x\right)\end{aligned} \tag{1.12}$$

$$\xi_{t}(x)=\left(\frac{v_{t+\Delta}\left(x+\lambda\right)-v_{t+\Delta}\left(x\right)}{w_{t}c_{own}}\right)^{\epsilon_{own}} \tag{1.13}$$

$$\zeta_t(x) = \left(\frac{\left(p_{t+\Delta} + (1-p_{t+\Delta})F_t(x)\right) v_{t+\Delta}(x)}{w_t c_{exp}} \right)^{\epsilon_{exp}} \tag{1.14}$$

$$\chi_t = \left(\frac{\int \left(p_{t+\Delta} + (1-p_{t+\Delta})F_t(x+\lambda)\right) v_{t+\Delta}(x+\lambda) dF_t\left(x\right)}{w_t c_{entry}} \right)^{\epsilon_{entry}} \tag{1.15}$$

In this equation system, $w_t := W_t/Y_t$ is not constant on the transition path.

The distribution along the transition path is expressed as the following equation:

$$\begin{aligned} F_{t+\Delta}(x) = {} & \Delta f_t(x) g_x x + F_t(x) - \Delta\delta F_t(x + g_{x,t}x\Delta) \\ & - \int_{s \in (x+\Delta g_{x,t}x-\lambda, x+\Delta g_{x,t}x]} \Delta \xi_t(s) dF_t(s) \\ & - \Delta\left(1-p_{t+\Delta}\right)\left(G_{t+\Delta}(\infty) - G_{t+\Delta}(x)\right)F_t(x) \\ & + \Delta p_{t+\Delta} G_{t+\Delta}(x), \end{aligned} \tag{1.16}$$

where

$$G_{t+\Delta}(x) = \int_{s \le x} \zeta_t(s) dF_t(s) + \int_{s \le x-\lambda} \chi_t dF_t(s) \tag{1.17}$$

$$\tau_{t+\Delta}\left(x\right) = \left(1-p_{t+\Delta}\right)\left(\chi_t \left(\int_{s>x-\lambda} dF_t(s)\right) + \int_{s>x} \zeta_t(s) dF_t(s)\right) \tag{1.18}$$

$$\delta = p_{t+\Delta} \int \zeta_t(s) dF_t(s) + \chi_t p_{t+\Delta}. \tag{1.19}$$

The sequences of prices w_t and r_t clear the markets for labor and the goods, respectively.

$$w_t = \left(\frac{\sigma-1}{\sigma}\right) / \left(L^s(w_t) - \int_{\Omega_t} c_{own}(\xi_{it}) di - \int_{\Omega_t} c_{exp}(\zeta_{it}) di - c_{entry}\left(\chi_t\right)\right) \tag{1.20}$$

$$r_t = \frac{C_{t+\Delta} - C_t}{C_t} + \rho, \tag{1.21}$$

$L^s(w_t) = (w_t/\phi)^\eta$ is the labor supply curve from the first order condition of the representative household. Lastly, the depreciation rate for x can be expressed as the following equation.

$$g_{Y,t+\Delta} = g_{A,t+\Delta} - g_{w,t+\Delta} \tag{1.22}$$

$$\begin{aligned} g_{x.t+\Delta} &= (\sigma - 1)\, g_{A,t+\Delta} = g_{Y,t+\Delta} + g_{w,t+\Delta} \\ &= \underbrace{\int \left[\int_{s\in(x-\lambda,x]} \xi_t(s)dF_t(s) \right] dx}_{=:(\sigma-1)g_t^{own}} \\ &\quad + \underbrace{p_{t+\Delta} \int \int_{s>x} \zeta_t(s)dF_t(s)dx - p_{t+\Delta}\bar{\zeta}_t}_{=:(\sigma-1)g_t^{exp(1)}} \\ &\quad + \underbrace{p_{t+\Delta} \int \chi_t \int_{s>x-\lambda} dF_t(s)dx - p_{t+\Delta}\chi_t}_{=:(\sigma-1)g_t^{entr(1)}} \\ &\quad + \underbrace{(1-p_{t+\Delta}) \int \left(\int_{s>x} \zeta_t(s)dF_t(s) \right) F_t(x)dx}_{=:(\sigma-1)g_t^{exp(2)}} \\ &\quad + \underbrace{(1-p_{t+\Delta}) \int \left(\chi_t \int_{s>x-\lambda} dF_t(s) \right) F_t(x)dx}_{=:(\sigma-1)g_t^{entr(2)}} \end{aligned} \tag{1.23}$$

In this equation, $g_{Y,t+\Delta} = (C_{t+\Delta} - C_t)/C_t$, $g_{w,t} = (w_{t+\Delta} - w_t)/w_t$, and $\bar{\zeta}_t := \int \zeta_t(s)dF_t(s)$. The equilibrium on the transition path is defined as the sequence of the value function $v_t(x)$; the policy functions $\xi_t(x)$, $\zeta_t(x)$; the product line distribution $f_t(x)$; the creative destruction rate $\tau_t(x)$; the depreciation and growth rates $\mu_{x,t}$ and $\mu_{Y,t}$; the entry rate χ_t; as well as the paths for wages w_t and interest rates r_t such that

1. The value function and the policy function satisfy the limit of Equations (1.12)-(1.14) when $\Delta \to 0$.

2. The distribution function satisfies the limit of Equations (1.16)-(1.19) when $\Delta \to 0$.

3. The price schedule satisfies the limit of Equations (1.20) and (1.21) when $\Delta \to 0$.

4. The depreciation and the growth rates are consistent with the limit of Equations (1.22) and (1.23) with $\Delta \to 0$.

5. The path of entry rates satisfies Equation (1.15) with $\Delta \to 0$.

The algorithm to find the equilibrium along the transition path is as follows:

1. Fix T, a very large number. I set $T = 100$ years. This will be where the economy converges (approximately) to the new BGP.

2. Start with an arbitrary sequence for w_t, r_t, g_t, p_t, $\tau_t(x)$, and $f_t(x)$.

3. Given the rest, update $v_t(x)$, $\xi_t(x)$, $\zeta_t(x)$, and χ_t backward from $t = T$ to $t = 0$. Notice that the value at $t = T + \Delta$ will be the value at the new BGP.

4. Given the updated policy function, update $f_t(x)$, $\tau_t(x)$, and p_t forward from $t = 0$ to $t = T$. Notice that the initial f_t at $t = 0$ is the distribution at the old BGP.

5. Given the updated policy and distribution function, update w_t, r_t, and g_t forward, using Equations (1.20), (1.21), and (1.23), respectively. Go back to step 3 until they converge.

After the computation, we get $\{Y_t^{BS}\}_{t=0}^{T}$ and $\{Y_t^{TR}\}_{t=0}^{T}$ as our baseline and transition paths, respectively. Then, we can calculate the welfare of each path evaluated at time 0. Let W_0^{BS} and W_0^{TR} denote the welfare of the representative household on the baseline and the transition paths, respectively. The two metrics in Table 1.6 are defined by the following equations. The first equation defines the initial change of output in the transition path equilibrium. The second equation defines the catch-up point.

$$\Delta Y_0/Y_0^{BS} := \left\{Y_0^{TR} - Y_0^{BS}\right\}/Y_0^{BS}$$
$$t|Y_t^{TR} = Y_t^{BS} := \inf\left\{t \geq 0|Y_t^{TR} \geq Y_t^{BS}\right\}$$

Next, the consumption-equivalent variation (CEV) is derived by the following equations:

$$\begin{aligned}
W_0^{TR} &= \int_0^{\infty} e^{-\rho t} \log\left(\left(1+CEV\right)Y_t^{BS}\right) dt \\
&= W_0^{BS} + \log\left(1+CEV\right)\int_0^{\infty} e^{-\rho t} dt \\
&= W_0^{BS} + \frac{\log\left(1+CEV\right)}{\rho} \\
\Rightarrow CEV &:= \exp\left(\rho\left(W_0^{TR} - W_0^{BS}\right)\right) - 1
\end{aligned}$$

I further decompose the change in welfare into own-product improvement, product expansion, and entrant innovation margins in the following way:

$$
\begin{aligned}
W_0 &:= \int_0^\infty e^{-\rho t} \log\left(e^{\int g_{Y,s} ds} Y_0\right) dt - \int_0^\infty e^{-\rho t} \frac{\phi L_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}} dt \\
&= \int_0^\infty e^{-\rho t} \int_0^t g_{Y,s} ds dt + \int_0^\infty e^{-\rho t} \log Y_0 dt - \int_0^\infty e^{-\rho t} \frac{\phi L_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}} dt \\
&= \int_0^\infty e^{-\rho t} \int_0^t g_s^{own} ds dt + \int_0^\infty e^{-\rho t} \int_0^t \left(g_s^{exp(1)} + g_s^{exp(2)}\right) ds dt \\
&\quad + \int_0^\infty e^{-\rho t} \int_0^t \left(g_s^{entr(1)} + g_s^{entr(2)}\right) ds dt + \text{other terms} \\
CEV &\approx \rho\left(W_0^{TR} - W_0^{BS}\right) \\
&= \rho\left(\int_0^\infty e^{-\rho t} \int_0^t \left(g_s^{own,TR} - g_s^{own,BS}\right) ds dt\right) \\
&\quad + \rho\left(\int_0^\infty e^{-\rho t} \int_0^t \left(g_s^{exp(1),TR} + g_s^{exp(2),TR} - g_s^{exp(1),BS} - g_s^{exp(2),BS}\right) ds dt\right) \\
&\quad + \rho\left(\int_0^\infty e^{-\rho t} \int_0^t \left(g_s^{entr(1),TR} + g_s^{entr(2),TR} - g_s^{entr(1),BS} - g_s^{entr(2),BS}\right) ds dt\right) \\
&\quad + \text{residuals}
\end{aligned}
$$

In this equation, superscripts BS and TR indicate that variables are evaluated at the baseline BGP and over the transition path, respectively. Then, I define the following metrics in Table 1.6, where Δg_0^{own}, Δg_0^{exp}, Δg_0^{entry} are the contributions of own-product improvements, product expansion, and entrant innovation to the welfare change, respectively:

$$
\begin{aligned}
\Delta g_0^{own} &:= \rho\left(\int_0^\infty e^{-\rho t} \int_0^t \left(g_s^{own,TR} - g_s^{own,BS}\right) ds dt\right) \\
\Delta g_0^{exp} &:= \rho\left(\int_0^\infty e^{-\rho t} \int_0^t \left(g_s^{exp(1),TR} + g_s^{exp(2),TR} - g_s^{exp(1),BS} - g_s^{exp(2),BS}\right) ds dt\right) \\
\Delta g_0^{entr} &:= \rho\left(\int_0^\infty e^{-\rho t} \int_0^t \left(g_s^{entr(1),TR} + g_s^{entr(2),TR} - g_s^{entr(1),BS} - g_s^{entr(2),BS}\right) ds dt\right)
\end{aligned}
$$

Table 1.14: Changes in Key Moments under Alternative Elasticity Values

	Baseline	$\eta = 0.3$	$\eta = 4$	$\epsilon_\chi = 0$	$\epsilon_\chi = 1$
Change in Growth (ppt)	0.10	0.10	0.11	0.10	0.10
Change in Wage	0.029	0.039	0.020	0.042	0.027
Change in Own-Improvement (ppt)	3.39	3.23	3.55	3.18	3.42
Change in Product Expansion (ppt)	0.10	0.10	0.10	0.09	0.11
Change in Job Creation (ppt)	1.74	1.81	1.83	1.81	1.68
Change in Job Destruction (ppt)	0.20	0.17	0.19	0.20	0.23
Initial Output Change (%)	-2.65	-3.46	-1.80	-3.86	-2.44
Catch-up Point (years)	24.2	33.1	15.7	37.3	23.2
Consumption Equivalent Variation (%)	2.07	1.54	2.72	0.21	2.20
Contribution of Own-Improvement (%)	2.71	2.59	2.83	2.54	2.76
Contribution of Product Expansion (%)	0.47	0.44	0.49	0.44	0.44
Contribution of Entry Innovation (%)	0.13	0.12	0.14	0.14	-0.01

Notes: The baseline assumes $\eta = 1$ and $\epsilon_{entry} = 0.1$. The columns that start with η assumes those values for η with $\epsilon_{entry} = 0.1$, and the others starting with ϵ_{entry} assumes the values for ϵ_{entry} with $\eta = 1$. The first panel shows changes between two BGPs. The second and the third panels summarize changes on the transition path. Catch-up point means the years needed for the transition economy with R&D incentives to catch up with the baseline BGP. The Consumption Equivalent Variation (CEV) is a permanent increase in consumption for the representative household in the baseline economy to have the same lifetime utility as in the transition economy. The bottom three lines are the contribution of each innovation margin to the CEV.

1.C.2 Alternative Frisch Labor Supply and Entry Elasticity

I assume $\eta = 1$ and $\epsilon_{entry} = 0.1$ for the baseline results. In this section, I test with alternative values for the Frisch elasticity of labor supply and establishment entry and reiterate the full R&D subsidy exercise. Values for labor wedge and entry cost shifter are adjusted for each elasticity value to match the BGP rates. When $\epsilon_{entry} = 0$, I assume the entry rate is fixed at the BGP, and the entrant innovation does not consume any labor. Table 1.14 shows changes in key BGP and transition path moments across different elasticity values. Almost all statistics stay almost the same over different values of elasticities, except the wage and the consumption equivalent variation (CEV). The wage increases more, and the CEV is larger with a lower η because the representative households respond less to the incentive change.

The higher entry elasticity (ϵ_{entry}) is associated with smaller wage responses because incumbent innovation crowds out entrant innovation more, reducing the labor used for entrant innovation. As a result, the output decreases after R&D incentives are smaller, and it takes a shorter time for the subsidized economy to catch up with the old BGP. The welfare effect is larger in this case with a lower entrant innovation rate. Similar to product expansion, entrant innovation also has the business stealing effect. In the calibrated model, the negative externalities from business stealing are so large that this crowd-out effect is welfare-enhancing. Even without endogenous changes in entry rates, in column $\epsilon_{entry} = 0$, the contribution of entry innovation to welfare change is positive because of increases in average step size of entrant innovation with more frequent own-product improvements. More frequent own-product improvements increase the dispersion of average quality. With more dispersion in the quality space, the average step sizes of product expansion and entrant innovation become larger, increasing their contribution to productivity growth.

1.D Application: the Hartz Reform and Innovation

1.D.1 Hartz Reform and Aggregate Moments

This section explains the details of the Hartz reform and shows the aggregate time series before and after the reform preceding model application in Section 1.D.2. The Hartz reform is a large-scale labor market reform that started in the early 2000s. The reform took four stages (Hartz I, II, III, and IV). The first stage of the reform took effect on January 1, 2003, and the last stage of the reform came into effect on January 1, 2005.

The Hartz reform had three cornerstones [31]. First, the reform improved the efficiency of government employment services. Government employment agencies were restructured during the reform, and the market-based mechanism was introduced to choose private employment agencies. Second, the reform incentivized unemployed workers to find a job by reorganizing the benefits system and requiring proactive actions from unemployed workers to receive the benefits. The reform also subsidized low-income wage earners. Lastly, the reform deregulated the labor market by expanding temporary work contracts and reducing firm size restrictions on dismissal protection.

I show that the reform affected the output growth and the welfare of the economy not only by increasing production inputs in the short run but also by accelerating long-run productivity growth. Because of its scope and depth in restructuring public employment agencies, the unemployment benefit system, and employee protection, the Hartz reform has been considered one of the most important changes in the labor market system in post-war Germany. However, most papers focus on the static impact of the reform on employment, wage, and welfare. [36] study the effectiveness of the Hartz reform using a search and matching model of the labor market. They conclude that the Hartz reform reduced the steady-state unemployment rate by 2.8 percentage points. More recent studies such as [37], [38], [11], and [28] also model frictional labor markets to quantitatively assess the effect of the reform. I consider the innovation choice of establishments to be another mechanism through which the reform affects welfare. The labor market reform affects R&D costs and future returns to innovation by increasing labor supply and removing labor market rigidity. Then, an increase in innovation may improve the welfare of the representative household in a world with positive externalities of innovation.

The German economy indeed enjoyed a larger increase in employment, output per capita, and labor productivity after the reform. As in Figure 1.14, the economy experienced a sharp increase in employment among workers aged 20-64 after the reform. The increases in employment rates were even steeper because the working-age population steadily decreased during that time. At the same time, after the Hartz reform I, II, III, and IV in the mid-2000s, the German economy grew faster than in the early 2000s both in terms of output per capita and labor productivity (See Figure 1.15).

However, unlike the Schumpeterian predictions that more growth comes from establishment-level replacements[27], job destruction rates decreased in Figure 1.16 during the periods of high aggregate output growth after the reform[28]. Consistent with the aggregate employment growth, more jobs were created after the reform. Even after employment peaked and growth slowed down in the post-2014 period, growth rates remained high, and job destruction rates stayed low. This is consistent with the hypothesis that the type of innovation that led to the fast economic growth in late 2014 was made by incumbent firms on their previous product portfolios, which did not require large job destruction at the establishment level.

27. For more discussions, see [12].

28. In the extensive margin, establishment exit rates also decreased during the same period.

Figure 1.14: Employment before and after the Hartz reform

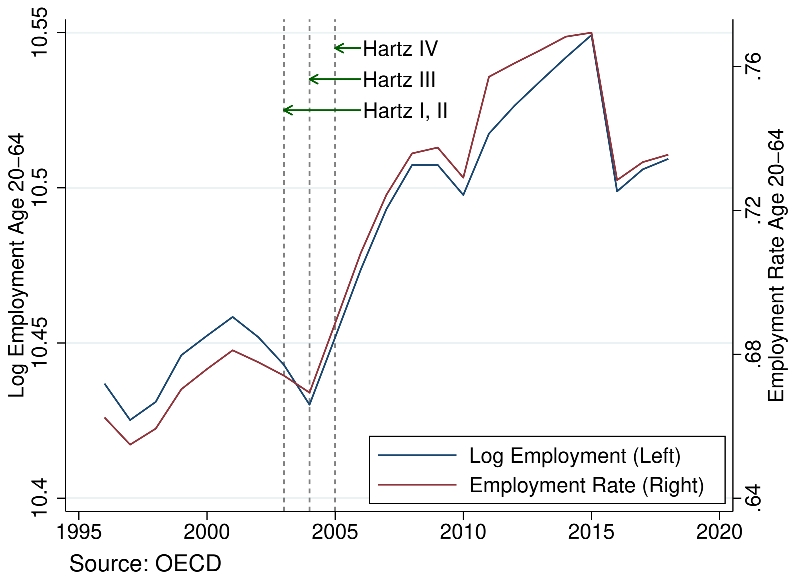


Figure 1.15: GDP growth before and after the Hartz reform

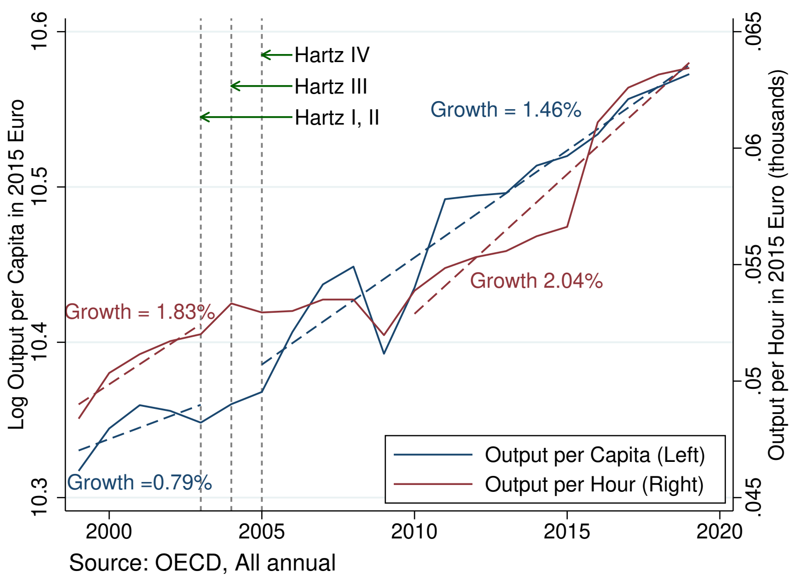
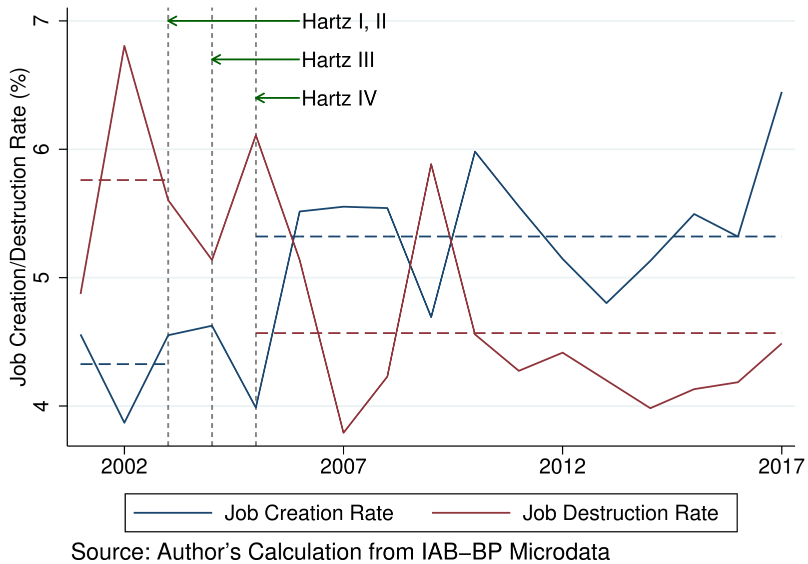


Figure 1.16: Job Creation and Destruction Rates



1.D.2 Interpretation of the Hartz Reform

I interpret the institutional components of the Hartz reform described in Appendix 1.D.1 in the context of the model. First, I assume that the Hartz reform is an exogenous increase in labor supply through a decrease in labor wedge in the representative household's problem. This interpretation is associated with the modernization of federal employment agencies and improving work incentives. The labor supply decision of the representative household now has the following wedge, ω_L. This is consistent with a linear labor income tax that is redistributed with a lump-sum transfer.

$$\phi\,(L_t^s)^{\frac{1}{\eta}} = (1-\omega_L)w$$

The values for the labor wedge before and after the Hartz reform are assumed to be strictly positive and zero, respectively. The value of the labor wedge in the pre-reform period is set to match the increase in labor supply between the early 2000s and the late 2010s. According to the Annual Labour Statistics by the OECD, the average national employment of the population aged 20-64 between 2000-2004 was 34 million in Germany and grew to 37 million (7.6%) in the late 2010s. Meanwhile, that same German population (age 20-64) decreased by 2.5%, from 51 million to 50 million. I interpret the 10 percentage points additional increase in employment as the effect of Hartz reform and set the labor wedge before the Hartz reform to match this increment. The baseline Frisch elasticity of labor supply is one. Under this parameter value, the implied labor wedge before the reform is 17%.

Second, I interpret the other effect of reform as lowering the cost of unexpected product line closures, which is associated with severance pays and administrative firing costs to the workers. Specifically, I include the following closure cost term in the value function.

$$
\begin{aligned}
(\rho + \delta + \tau(x))\, v(x) = \max_{\xi,\zeta \geq 0} \Bigg\{ & \pi(x) - g_x x v'(x) \\
& - w c_{own}(\xi) + \xi \left(v\left(x + \lambda^i \bar{x} \right) - v(x) \right) \\
& - w c_{exp}(\zeta) + \zeta (p + (1-p) F(x))\, v(x) \\
& - (\tau(x) + \delta) \underbrace{\kappa x}_{\text{line closure cost}} \Bigg\}
\end{aligned}
$$

For simplicity, I assume that the closure cost increases linearly in x and does not depend on the actual employment[29]. This cost is summarized as κ in the model. The severance pay is around 50% of the monthly wage per tenure year, and the mean tenure of a German worker is 10 years. There are not many studies estimating firing costs in Germany, but a

29. If the cost of unexpected product line closures depends on the actual employment, then the dynamic problem of establishments would need an additional state variable on employment size, which complicates the analysis. By introducing this assumption, I ignore an additional employment gain from the Hartz reform in hiring more production labor at the same quality level and in hiring more R&D labor with returns to own-product improvements and product expansion increased due to that production margin. Thus, this model is likely to underestimate gains from the Hartz Reform.

paper by [8] estimated that the firing cost corresponds to 75% of annual wages in Germany. A product line with x hires $\frac{\sigma-1}{\sigma}x/w$ and $c_{exp}(\zeta(x)) + c_{own}(\xi(x))$ units of production and R&D labor, respectively. Assuming R&D labor demand is proportional to x as well, $\kappa = (10 \times 0.5 + 0.75 \times 12) \times L \approx 4.99$ before the reform, and $\kappa = 0$ after the reform. As in the paper, I set the Frisch elasticity of labor supply to one and the entry elasticity to 0.1.

1.D.3 Balanced Growth Path

Table 1.15 compares the BGP moments before and after the Hartz reform. The first column summarizes the BGP before the Hartz reform while the fourth column summarizes the BGP after the Hartz reform. To separate the effect of an exogenous increase in labor supply with the effect of removing firing costs, the second column summarizes the new BGP after removing the labor wedge without reducing κ. Similarly, the third column fixes the positive labor wedge and only reduces κ to zero.

The labor wedge margin is more important in accelerating productivity growth across different BGPs than the firing cost margin. This is because, while the increase in labor supply decreases the wage paid by establishments, the reduction of firing cost increases the wage level. This wage increase after removing firing costs is a result of more labor demand for R&D. However, without a further increase in labor supply, innovation rates cannot increase significantly. The decrease in wage after removing the labor wedge is important in reducing innovation costs and boosting incumbents' innovation behavior. Reducing firing costs contributes to a higher frequency of own-product improvements, product expansion, and entrant innovation, but the impact on growth is small.

The reform overall increases incumbent innovation rates per product line. Akin to the R&D incentives, the increase is more pronounced for own-product improvements. The average own-product improvement rate increases 1.5 percentage points per year, while the average product expansion rate increases only by 0.05 percentage points. Moreover, the job creation and destruction rates barely change across the different BGPs with small responses in the product expansion rate.

Table 1.15: Effect of the Hartz Reform on the new BGP

	Pre	No Labor Wedge	No Firing Cost	Post
Output Growth Rate	1.33	1.37	1.33	1.37
Wage	1.093	0.997	1.097	1.000
Own-Product Improvement Rate	43.6	45.1	43.7	45.1
Product Expansion Rate	0.80	0.84	0.81	0.85
Entry Rate	1.19	1.20	1.19	1.20
Job Creation Rate	1.40	1.48	1.42	1.52
Job Destruction Rate	0.87	0.91	0.88	0.91

Notes: All in %, except Wage. All flow rates are annual. The innovation rates are defined per product line and calculated conditional on successful innovation. Thus, q_{own} and q_{exp} are multiplied with $\xi(x)$ and $\zeta(x)$, respectively, before taking average over the distribution of x.

1.D.4 Transition Path

On the transition path, I assume an exponentially decreasing labor wedge and firing costs after the unexpected policy introduction at $t = 0$. Motivated by the fact that the reform (Hartz I, II, III, and IV) was implemented over three years, I set the exponent to decrease linearly so that the values of the labor wedge and the firing cost parameters at $t = 36$ months become 1% of the pre-reform level. This gives me 12% as the decaying rate for a month. Additionally, I set the initial labor wedge and the firing cost parameters at $t = 0$

as $\exp(-0.12) = 88\%$ of the BGP level. Figure 1.17 describes the resulting path for labor wedge and firing cost parameters.

Figure 1.17: Labor Wedge and Firing Cost under the Hartz Reform Transition

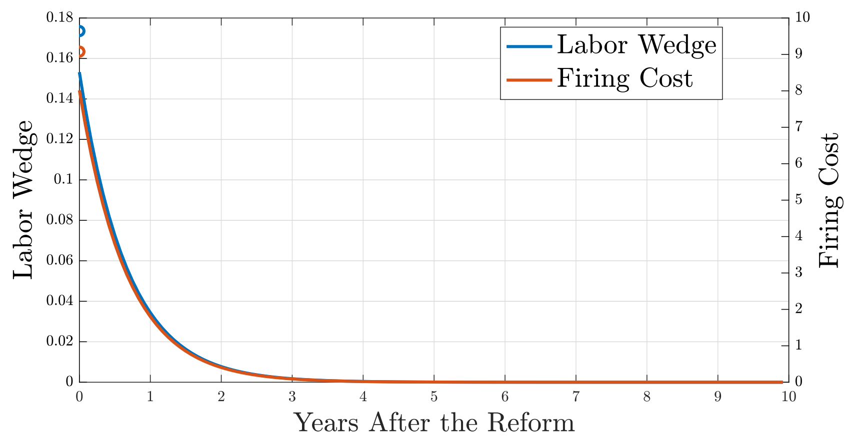


Figure 1.18 shows the increase in output relative to the pre-reform BGP. The decrease in labor wedge is quantitatively more important than the decrease in firing costs. With the increases in labor supply, the output jumps up initially after the reform in time 0 and grows further with the decaying labor wedge. Moreover, it also grows faster than the pre-reform BGP because of more innovation (see Figure 1.19). On the transition path, it is also the own-product improvement margin that contributes the most to output growth. Product expansion and entrant innovation have a positive but limited role in promoting output growth.

Without an exogenous increase in labor supply, the economy experiences an initial drop in output production (as shown by the yellow line in Figure 1.18) because more labor inputs are used for R&D. Furthermore, the economy experiences a virtually permanent output drop after removing the firing costs[30]. This reduction in output results from more innovations

30. With a higher productivity growth on the new BGP compared to the old BGP, the transition economy eventually catches up with the old economy after 103 years.

that consume labor for R&D but fail to improve productivity growth. Product expansion and entrant innovations consume too much labor compared to their growth impacts because of the business stealing effect described in Section 1.D.4. Therefore, the economy is worse off by only removing firing costs. This negative welfare effect also happens after removing firing costs for the same reduction in the labor wedge.

Figure 1.18: Relative Log Output under the Hartz Reform Transition

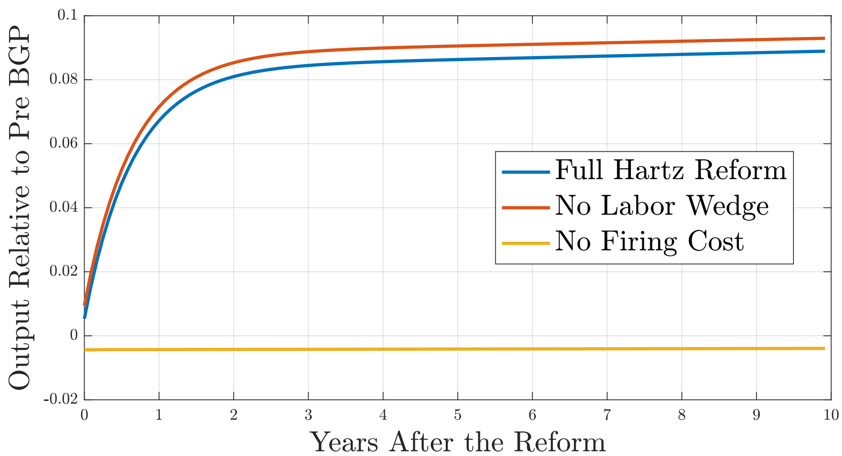


Figure 1.19: Relative Contribution to Output under the Hartz Reform Transition

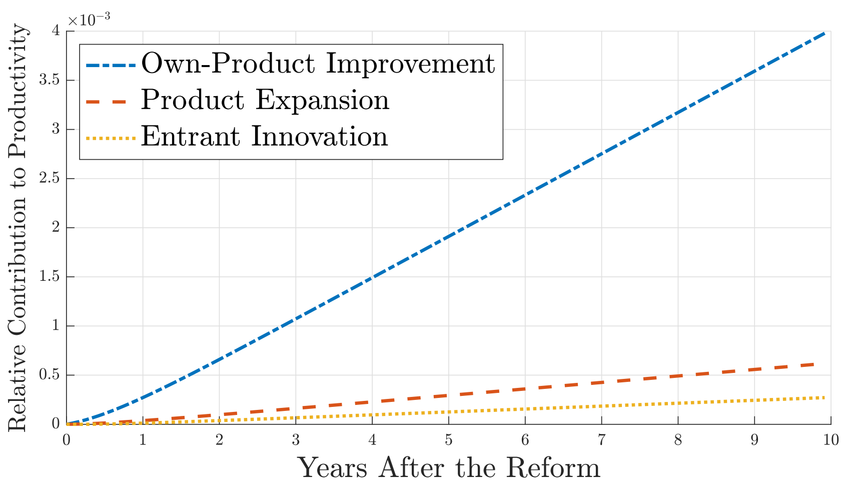
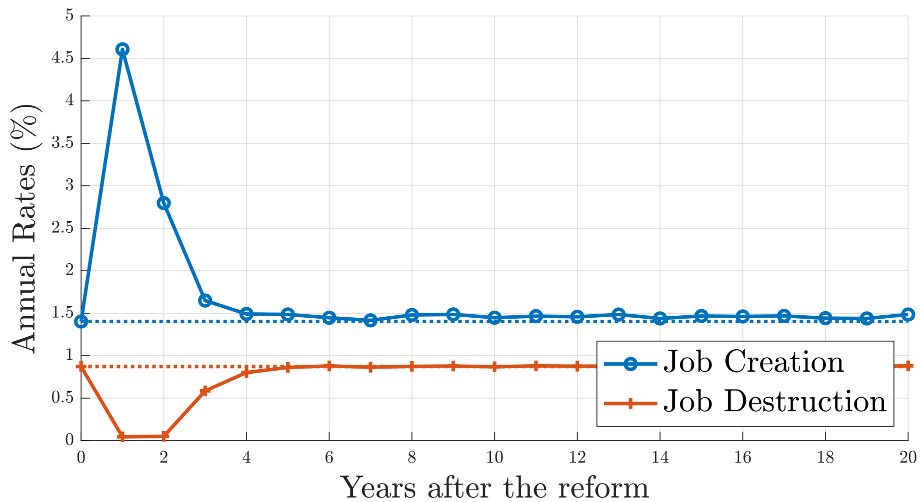


Figure 1.20 describes the changes in job creation and destruction rates calculated with simulated panels over the transition path. Because of a sharp reduction in labor wedge

and wage at the onset of the reform, even non-innovating establishments contribute to job creation in the short run after the reform. Consequently, in the short run after the reform, job creation increases but job destruction decreases. Over the transition path, as wage reduction becomes smaller, job creation and destruction rates become close to the pre-reform levels (see the dotted lines in blue for job creation and orange for job destruction).

Figure 1.20: Job Creation and Destruction Rates over the Transition Path



Notes: Job creation and destruction rates over the transition path are calculated from simulated panels.

The third column of Table 1.16 shows that the welfare effect of Hartz reform is equivalent to a permanent 4.95% increase in the consumption schedule of the representative household in the pre-reform BGP. Productivity growth from more own-product improvements is still the most important factor of the welfare increase among the three innovation margins. The dynamic gains from faster output growth after the Hartz reform accounts for 31% (1.51/4.95) of the entire increase in welfare, while the remainder originates from the static increase in production labor after the reform. Own-product improvements account for 81% (1.23/1.51) of dynamic gains from the reform. Consistent with the output results over the transition path, the reduction in the labor wedge plays a dominant role in improving welfare. Without increases in labor supply, removing firing costs reduces the welfare because additional R&D activities, especially entrant innovation, soak up too much production labor without boosting productivity growth. Again, this result comes from the negative externalities of entrant innovation through stealing the business of incumbent producers.

Table 1.16: Effect of the Hartz Reform in the Transition Path

	No Labor Wedge	No Firing Cost	Post
Initial Output Change	0.95	-0.44	0.54
Consumption Equivalent Variation	5.48	-0.45	4.95
Own-Product Improvement	1.14	0.09	1.23
Horizontal Innovation	0.18	0.01	0.19
Product Expansion	0.08	0.00	0.09
Entrant Innovation	-5.09	-0.20	-5.32

Notes: All in %. The Consumption Equivalent Variation is a permanent increase in consumption for the representative household in the baseline economy to have the same lifetime utility as in the transition economy. Own-Product Improvement, Product Expansion, and Entrant Innovation are the contributions of each innovation type to welfare change. The rest of welfare change comes from changes in labor supply over the transition path. For the derivations, see Appendix 1.C.1.

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