Do Firms or Industries Matter for Productivity Growth? An Analysis of Swiss Manufacturing[☆]

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Abstract

We develop a framework to decompose aggregate productivity growth into contributions from inter- and intra-industry reallocations of sales shares across firms. Applying this framework to a novel data set of Swiss manufacturing firms, we investigate whether growth was driven by a Ricardian-type specialization towards industries of comparative advantage or by reallocations within industries towards the most productive firms as emphasized by the trade literature on heterogeneous firms. Our findings suggest that both effects have been at work in Swiss manufacturing, although predominantly focussed on the chemicals industry. That said, the exceptional growth of this industry has masked stagnant productivity developments in much of Swiss manufacturing. This points at a number of policy challenges to better understand the different impact of growth enhancing policy measures across industries as well as to risks arising from further concentration of manufacturing growth on a limited number of industries.

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1. Introduction

Productivity growth is a driving force of economic welfare. It thus assumes a high priority on most economic policy agendas, acting as a key metric to gauge growth prospects and, in particular, international competitiveness. While individual firms will typically benchmark their productivity against leading competitors, policy makers face a variety of trade-offs in determining which productivity measures to track. For one, aggregate productivity measures may be easiest to track in terms of data availability. Observing productivity developments only at high levels of aggregation, however, may lead to misguided conclusions, if the sources of the growth dynamics are not fully understood. Specifically, rising aggregate productivity may reflect a general rise in productivity at the firm level. It may equally result from a shift in sales towards more productive industries (*inter*-industry) or a shift towards more productive firms within industries (*intra*-industry). Yet, the assessment—both from an economic, and sometimes quite differently from a political point of view—of a specific policy's success may well depend on whether it has been perceived to foster productivity throughout an industry or sector or whether productivity improvements are primarily attributable to the demise of individual industries or the exit of the least productive firms.

A key question is the level of disaggregation needed to adequately inform economic policy decisions. Increasing access to detailed firm-level data has renewed researchers' interest in the estimation of firm-level productivity[3] and has given rise to the development of both new models and econometric tools that specifically address firm heterogeneity in the context of international trade.[4] Whereas a major concern in the models is the role of productivity for firms' entry and exit decisions as well as shifts in production in response to changes in the economic environment, econometric tools

[3]Bartelsman and Doms (2000) provide a literature review of the empirical work.

[4]Examples of frequently cited models are Jovanovic (1982), Hopenhayn (1992), Eriscon and Pakes (1995), Melitz (2003), Bernard et al. (2003) and Yeaple (2005). We discuss the relevant econometric contributions in detail in section 3 as we illustrate our estimation strategy.

also emphasize the challenges arising from the endogeneity of the firms' input choice. Moreover, this branch of the international trade literature emphasizes within-plant productivity growth or within-industry reallocations of resources as a source of aggregate productivity growth in contrast to the traditional trade literature which focuses on across-industry specialization as a determinant of the gains from trade.[5]

In this paper, we design a framework to study the different sources of productivity growth, distinguishing productivity improvements in firm-level averages from those arising from inter-industry and intra-industry reallocations of sales in favor of more productive firms. This allows us to assess whether growth has been predominantly driven by a sector's specialization on its most productive industries, akin to the Ricardian argument of comparative advantage, or whether reallocations within industries, as emphasized by the trade literature of heterogeneous firms,[6] have had a stronger impact. We apply this framework to the example of a seemingly low-growth, advanced economy sector: Swiss manufacturing. The Swiss economy is an interesting example to study for several reasons.

First, while Swiss manufacturers are renowned for their innovation and high quality throughout the world, this impression sharply contrasts with a variety of studies arguing that Switzerland witnessed exceptionally poor productivity growth in the last decades. In fact, Kehoe and Prescott (2002) as well as Kehoe and Ruh (2005) allude to the Swiss economy as having experienced a great depression from 1974 to 2000 based on continuously falling output per working-age person. Similarly, Brunetti and Zürcher (2002) report low and continuously falling labor productivity (LAP) growth rates throughout several decades with the exception of the chemicals industry. According to their analysis, high levels of income have only been sustainable because the Swiss work a lot, i.e. because a lot of Swiss work and because they work long hours.[7]

[5] See for example Bernard et al. (2007).
[6] See Redding (2011) for an overview of the literature.
[7] See also Weber and Zürcher (2001) on p. 33.

Several studies have contested these alarming assessments. For one, Abrahamsen et al. (2005) question the appropriateness of the productivity measures employed in these studies. These authors cast a much more favorable view on Switzerland's productivity growth based on the development of GDP per hour worked, adjusting for terms of trade changes and investment in intangibles. Other examples include Hartwig (2008) and Siegenthaler (2012) who raise more general concerns about the quality of the time series relied on. Despite the jury on productivity developments still open, promotion of productivity growth has taken center stage in Switzerland's recent economic growth policy and triggered the implementation of a variety of structural reforms.[8]

Second, Switzerland is a small open economy with an extremely high degree of international integration. This international exposure is likely to amplify the dynamics (e.g. specialization) in productivity growth, leading us to expect sizable shifts both across and within sectors even in absence of large productivity improvements at the aggregate level.

Finally, from a purely empirical perspective, our study is the first to present a comprehensive data set on Swiss manufacturing firms. We thus provide a number of stylized facts of Swiss firms' characteristics, the way they produce and how their productivity has evolved over the years.

Despite the lively dispute about the assessment of productivity growth in Switzerland, the analysis of Swiss firms has lagged behind. A comprehensive analysis at the firm-level has been hampered by the lack of detailed firm-level data. Previous empirical work has improved our understanding of some aspects, including for example the determinants of innovation of Swiss manufacturing firms as in Arvanitis and Hollenstein (1994), Arvanitis (1997) or more recently in the cross-country studies of Roper and Arvanitis (2012) and Arvanitis and Bolli (2012).

[8]For more details on the Swiss government's federal growth policy see State Secretariat for Economic Affairs (2002), State Secretariat for Economic Affairs (2008b) and State Secretariat for Economic Affairs (2008a).

Other studies extend to the service sector looking at the role of computerization and work place organization as in Arvanitis (2005) or address internationalization of Swiss firms such as in Arvanitis and Hollenstein (2011). These studies, however, neither cover a sufficient range of years nor of firm-level information for a comprehensive assessment of productivity developments based on a structured estimation of total factor productivity (TFP) that is typically at the center of country studies.

Our paper aims to close this gap and to contribute to a better understanding of Swiss firms' productivity in several ways. First, we present a novel firm-level data set, covering some 2,000 Swiss manufacturing firms for each year from 1997 to 2009 with detailed insights into their economic activity and LAP (defined as real revenue divided by the number of employee full-time equivalents). Second, we estimate the firms' production functions to assess the contribution of key input factors to manufacturing production. This allows us base our aggregate TFP estimates on a bottom-up estimation of individual firm-level TFP, shedding light into the evolution of TFP from 1999 to 2009, a time of strong integration of the Swiss economy with the EU but also covering the Swiss recession of 2003 and the more recent slump in global economic activity of 2009.

At the aggregate level, our findings suggest that TFP in Swiss manufacturing rose by a timid 1.1% per year from 1999 to 2009, lending support to the more critical assessments of productivity growth in Switzerland. This figure, however, hides the pronounced differences across industries and firms. Notably, the chemicals industry (including pharmaceuticals) turns out to be the key driver of TFP growth since 2004. We find evidence for both an inter-industry and an intra-industry contribution to aggregate growth. While a rising share of production has shifted from less productive industries to the chemicals industry, productivity growth in chemicals is also promoted by a shift in production towards the most productive firms within this industry. We also observe that the largest part of the variation in aggregate productivity is linked to inter- or intra-industry movements, the latter effect being more important than the former.

Abstracting from developments linked to the chemicals industry, however, we find very limited evidence for any inter- or intra-industry dynamics. While the discrepancy in industry performance may underscore differences in the pace of international integration, it also questions the effectiveness of domestic growth promoting policy measures targeting the manufacturing sector as a whole.

LAP estimates cast a more favorable view on overall manufacturing performance, suggesting a yearly growth rate of 4.0% from 1999 to 2009. This finding is line with the more positive evaluations of economic performance mentioned above. As with TFP, however, industry differences stand out. Aggregate LAP rises on the back of reallocations both in favor of and within the chemicals industry. Yet, once we single out this industry our estimates unveil surprisingly little inter- and intra-industry dynamics.

Our sample also allows for a comparison of industry responses to the economic downturns of 2003 and 2009, with Swiss annual GDP slipping by 0.2% and 1.9% respectively. The 2009 contraction has likely had a much stronger impact on the export-oriented Swiss manufacturing sector, given the unprecedented fall in Swiss exporting and importing with all key trading partners observed at the time. Accordingly, we find that most manufacturing industries in Switzerland experienced sizeable drops in productivity as TFP decreased by 8% and LAP by 15% excluding the chemicals industry. The latter industry, however, proved surprisingly resilient to the 2009 downturn with TFP (LAP) growth of 15% (8%), a productivity increase that is partly due to substantial reallocations towards more productive firms in this industry.

The rest of our paper consists of five sections. Section 2 presents the new firm-level data of Swiss manufacturing and some insights. In Section 3 we outline our strategy in estimating TFP and discuss methodological issues to address potential biases in estimated production functions. In Section 4 we present the analytical framework to decompose aggregate levels of LAP and TFP into different sources of growth at the firm-level and reallocations across and within industries. Section 5 discusses the results and briefly evaluates whether stepping up Swiss economic integration into the European Union (EU) based on the Bilateral Agreements may be visible in our productivity estimates. We conclude the paper in section 6. The Appendix provides a detailed derivation of the different decompositions of productivity measures and describes the data.

2. New Firm-Level Data and First Insights

Our data set consists of an unbalanced panel of about 2,000 Swiss manufacturing firms for the years from 1997 to 2009. The data was collected and revised by the Swiss Federal Statistics Office (SFSO) and is based on an extensive questionnaire sent to firms each year.[9] Our data covers 22 different industries according to the 2-digit Swiss industry classification [10], which we group into 13 industries to combine similar industries and yield samples of meaningful size for estimation. A description of the data is given in the appendix. Table C.3 provides an overview of the industries and how they are mapped into the NOGA classification. Furthermore, the shares of these 13 industries in our sample as well as in official industry statistics with respect to nominal sales are given in the table, revealing that the chemicals (including pharmaceuticals) and the machinery industry are the largest Swiss manufacturing industries.

Data coverage varies substantially by measure. Compared to the Swiss Business Census the data set comprises only 5% of active firms, but these firms employ nearly half of the manufacturing sector's workforce.[11] This reflects the fact that three out

[9]Access to the data set was granted under strict confidentiality requirements. All necessary measures were taken to prevent identification of an individual firm's name at any stage of the analysis.

[10]NOGA 2002, exactly corresponding to ISIC 3.1

[11]The Swiss Business Census offers a comprehensive account of all Swiss firms but only records each firm's number of employees (with some refinements), its location and its main business activity based on the industry classification. The census data is thus insufficient for an in-depth analysis of productivity developments.

of four Swiss manufacturing firms employ less than 9 employees. These firms are thus clearly underrepresented in our sample. Furthermore, the firms in the sample contribute to about 60% of their industry's sales on average, with coverage ranging up to almost 80% in some industries. Table C.3 shows the extent of coverage of our data set with respect to the number of firms and the sales for each industry.

Table C.4 illustrates the main characteristics of the data, showing summary statistics by firm size (in terms of employees[12]) for the first year of our sample, 1997, and every fourth year up to 2009. As in many other country studies, a typical pattern arises: Larger firms pay higher (average) wages, employ more capital and intermediates per employee, and are more productive in terms of both LAP, measured as each firm's deflated revenue divided by labor input in terms of employee full-time equivalents. For example, LAP of large firms with more than 500 employees was 33% above average in 1997, whereas that of the smallest firms was 11% below average.

The distribution of average wages is remarkably stable throughout the 13 years of our sample. Most firms pay average wages close to the total manufacturing average, with the smallest firms about 5% below and large firms with 200 to 500 employees some 5% above the average in 1997. Only the largest firms with more than 500 employees stand out with substantially higher average wages than their smaller competitors. Moreover, average wages have been growing steadily in nominal terms from 1997 to 2009 for all categories of firms. A more detailed look at the data set implies that the mild recession of 2003 left no traces in nominal wages, but wages fell 2% on average during the stiff recession of 2009 with wages at the larger firms affected more than at the smaller ones (not shown in the table). The hefty decline in international trade during this recession may explain this observation, since both theory and empirical studies suggest that larger firms are more involved in international activities.[13]

[12]As a matter of readability we refer to employees in the paper, although, in technical terms, we always imply employee full-time equivalents.

[13]The results are similar for real wages, i.e. nominal wages deflated by the SFSO's wage indices.

Table C.4 also shows that larger firms rely heavily on capital and intermediates. In terms of capital per employee firms with more than 200 employees stand out in our sample. The gap between these firms and their smaller competitors has widened substantially since 1997. This is likely to be a leading factor for the sizable differences in LAP. In addition, the largest firms (> 500 employees) employ substantially more intermediates per employee than their smaller peers, contributing to the pronounced productivity advantage of these firms reported in the table.

The following sections are dedicated to putting more scrutiny to the assessment of these productivity differentials. In particular, we will investigate whether the observed increase in LAP of firms evaporates if we take into account the possible increase of the use of other factors of production such as capital. This requires to estimate total factor productivity (TFP) on the level of firms in Section 3. Section 4 will then investigate whether changes in LAP or TFP on the aggregate level is mainly due to a within-firm productivity increase or rather to a change in the specialization within or across industries. To do this, we propose a novel approach to decompose aggregate productivity measures.

3. Estimating Firms' Total Factor Productivity

To estimate TFP we first present the basic setup and then consider the necessary adjustments to address possible price biases (Subsection 3.2) as well as the endogeneity of input choices and sample selection issues (Subsection 3.3).

3.1. Basic Setup

Our ambition is to measure TFP for each firm in our sample. We rely on a simple Cobb-Douglas production function. Firm i, producing a unit of output Q_{ijt} at time t in industry $j \in J$, resorts to three factors of production: capital (K_{ijt}), labor (L_{ijt}) and intermediates (M_{ijt}). Whereas these inputs are generally observable in our data set, though only in nominal terms and possibly prone to measurement error, output also hinges on unobservable TFP, A_{ijt}.

To be clear, TFP is a residual measure accounting for the share of observed production that is not explained by the use of observed inputs. It captures the firm's ability to combine inputs in a productive manner with firms outperforming others in terms of TFP being referred to as more productive. In practical terms, A_{ijt} will capture unobservable features such as technology, labour skills and management quality. Yet TFP can, as an example, also be driven by unobservable swings in capacity utilization.[14] For the remainder of this paper, we refer to A_{it} as the firm's productivity as is common practice in the literature.

Let the production function be given by $Q_{ijt} = A_{ijt} K_{ijt}^{\alpha_k} L_{ijt}^{\alpha_l} M_{ijt}^{\alpha_m}$ with α_z for $z = \{k, l, m\}$ representing the elasticity of substitution of each input factor. The firm's productivity is assumed to consist of three components with the simplifying functional form $A_{ijt} = \exp(\alpha_0 + \omega_{ijt} + \varepsilon_{ijt})$. The term α_0 is a time-invariant measure of average productivity across firms, whereas ω_{ijt} represents the firm-specific productivity that is observable to the firm and (potentially) predictable by the researcher. The last term, ε_{ijt}, encompasses a random "shock" to productivity at the firm-level and any measurement errors. According to these assumptions, ω_{ijt} is the only source of systematic firm heterogeneity.[15] This simplification allows analyzing productivity developments based on a convenient measure and straightforward aggregation at the industry-level. Denoting natural logs of the inputs with lower-case letters, our basic estimation equation

[14]Consider the case of a typical Swiss firm employing workers on a 40-hour fixed based contract. In times of reduced demand for the company's products workers may be taking longer breaks during working hours. Given labor market rigidities, the firm may abstain from laying-off workers or cutting wages, thus leaving the sum of wages unaffected. The latter is typically used to proxy labor input. All else equal, the firm's TFP would decline as workers effectively work and produce less without the researcher having a chance to assign the drop in output to reduced labor input.

[15]This is a very convenient setting, but obviously a strong simplification as criticized by Gandhi et al. (2011)

becomes:

$$q_{ijt} = \alpha_0 + \alpha_k k_{ijt} + \alpha_l l_{ijt} + \alpha_m m_{ijt} + \omega_{ijt} + \varepsilon_{ijt}. \tag{1}$$

Van Beveren (2012) provides a thorough review of the potential sources that may bias the coefficient estimates of the production function in (1). The data at hand allow us to address three of them: The bias arising from (i) omitting firm-level prices, (ii) the endogeneity of the firm's input choices and (iii) sample selection. Whereas the correction for the bias arising from (ii) and (iii) is quite common, only a few studies take into account the bias from (i).[16]

3.2. Omitted Price Bias

Concerning the issue of omitting firm-level prices, note that the production function is based on physical units that typically cannot be observed directly in the data. In the absence of detailed information on a firm's output and input prices, hours effectively worked or capital utilization, researchers rely on industry-level or even national price indices to deflate the nominal values in the data. Approximating physical output, q_{ijt}, by revenues deflated at the industry-level, $\tilde{r}_{ijt} = q_{ijt} + p_{ijt} - p_{jt}$, where p_{ijt} and p_{jt} denote the logs of the firm's output price and the industry's price level, respectively, will bias the estimated coefficients in the production function if firm and industry prices differ. This is because variation in the firm's output price will correlate with the firm's input choice, an issue referred to as omitted price bias in the literature. De Loecker (2011) argues the correlation is typically negative (higher output prices leading to less production) and will thus bias the coefficients on (variable) inputs downwards. As shown in studies where researchers do have access to firm-level price information, deflating at the industry level can significantly bias estimated coefficients.[17]

Our data covers Swiss manufacturers from which we expect a high level of prod-

[16] Notable exceptions are, inter alia, Ornaghi (2006) and De Loecker (2011)

[17] See e.g. Ornaghi (2006) and Foster et al. (2008). By contrast, Mairesse and Jaumandreu (2005) report a very small bias in their study of French and Spanish firms.

uct differentiation and thus price variation within industries. Hence, we employ the method originating from Klette and Griliches (1996) to address the bias from omitting firm-specific output prices.[18] We introduce a specific demand system to our setting. Specifically, let demand for the single variety produced by firm i, operating in industry s, be given by the standard CES structure (in logs) $q_{ijt} = q_{jt} - \sigma_j \left(p_{ijt} - p_{jt}\right) + \upsilon_{ijt}$ where in addition to the variables defined before, q_{jt} is the industry's output (often referred to as demand shifter) and υ_{ijt} captures any independent and identically distributed (i.i.d.) demand shocks or measurement errors. Each firm sets an individual price p_{ijt} equal to its marginal cost of production times the industry-specific markup $\sigma_j/(\sigma_j - 1)$ with $\sigma_j > 1$ representing the elasticity of substitution between product varieties of the same industry. Since, as argued above, we observe a firm's revenue rather than the quantity produced or the firm's output price, we solve the demand function for the firm's price and rewrite the equation in terms of revenue deflated at the industry-level:

$$\tilde{r}_{ijt} = r_{ijt} - p_{jt} = \left(\frac{\sigma_j - 1}{\sigma_j}\right) q_{ijt} + \frac{1}{\sigma_j} q_{jt} + \frac{1}{\sigma_j} \upsilon_{ijt}. \tag{2}$$

We substitute equation (1) into (2) and summarize terms to obtain:

$$\tilde{r}_{ijt} = \beta_0 + \beta_k k_{ijt} + \beta_l l_{ijt} + \beta_m m_{ijt} + \beta_j q_{jt} + \omega^*_{ijt} + \varepsilon^*_{ijt}, \tag{3}$$

with the coefficients of interest given by $\beta_z = \left(\frac{\sigma_j - 1}{\sigma_j}\right) \alpha_z$ for $z = \{0, k, l, m\}$ and $\beta_j = \frac{1}{\sigma_j}$. The latter allows identifying the elasticity of substitution. Furthermore, $\omega^*_{ijt} = \left(\frac{\sigma_j - 1}{\sigma_j}\right) \omega_{ijt}$ and i.i.d. shocks are summarized in $\varepsilon^*_{ijt} = \left(\frac{\sigma_j - 1}{\sigma_j}\right) \varepsilon_{ijt} + \frac{1}{\sigma_j} \upsilon_{ijt}$. Calculation of TFP estimates at the firm-level implies accounting for the estimated

[18] Our data does not allow, however, to correct for firm-specific input prices as, to the best of our knowledge, no general strategy exists to do so in the absence of firm-level price information. De Loecker (2011) argues, however, that as long as higher input prices are reflected in higher output prices, then taking account of the omitted price bias will at least partially remedy the bias.

markup in each industry:

$$\hat{\omega}_{ijt} + \hat{\alpha}_0 = \left(\frac{\hat{\sigma}_j}{\hat{\sigma}_j - 1}\right)\left(\tilde{r}_{ijt} - \hat{\beta}_k k_{ijt} - \hat{\beta}_l l_{ijt} - \hat{\beta}_m m_{ijt} - \hat{\beta}_j q_{jt}\right). \qquad (4)$$

We can retrieve industry-specific elasticities either by running the regression on firm data for each industry separately or, to benefit from pooling, by replacing $\beta_j q_{jt}$ by $\sum_{j=1}^{J} \beta_j q_{jt} I_{ij}$ where I_{ij} is a dummy variable of unit value (else zero) if firm i is active in industry j.[19]

3.3. Endogeneity of Input Choices and Sample Selection

We now focus on the bias arising from the endogeneity of input choices. Such a bias may arise if the firm adjusts its use of inputs in response to the productivity change its management observes. In this context, an OLS regression of (3) would yield biased coefficients.

To recover the firm's productivity, we follow the basic procedure outlined in Ackerberg et al. (2006), henceforth ACF, while also controlling for sample selection. This procedure is robust to identification issues potentially arising in the widely used procedures of Olley and Pakes (1996) and Levinsohn and Petrin (2003), referred to as OP and LP in the following. We report results on OP and LP in the discussion of our regression results for comparison.[20]

ACF impose an explicit timing assumption. Each firm decides whether to invest or not at $t-1$, thereby fixing the level of available capital at t, k_{ijt}. In the intermediate period $t-b$ with $0 < b < 1$, the firm chooses the amount of labor it will employ at t, l_{ijt}. Finally, at time t, the firm selects the intermediates it uses, m_{ijt}.

[19] In principle, this setup allows for a firm to face up to J different demand functions. Yet in difference to the study of for example De Loecker (2011), a single firm's activity in our data set is always assigned to exactly one industry.

[20] The literature has brought about a great variety of techniques to estimate TFP. In this paper, we limit ourselves to parametric and semi-parametric estimators and refer to Van Biesebroeck (2007) and Van Biesebroeck (2008) for a discussion of non-parametric techniques such as index numbers and data envelopment analysis.

Productivity evolves according to a first-order Markov process between these time periods. We thus have $\omega_{ijt-b} = E\left(\omega_{ijt-b}|\omega_{ijt-1}\right) + \xi_{ijt-1}$ and $\omega_{ijt} = E\left(\omega_{ijt}|\omega_{ijt-b}\right) + \xi_{ijt-b}$ with ξ_{ijt} representing the innovation to the firm's productivity at time t. This implies that firms base their expectations about future productivity only on given productivity levels. The firm's investment decision in t, i_{ijt}, will therefore rely on the firm's given capital stock, k_{ijt}, contemporaneous labor employed, l_{ijt}, as well as the most recently observed productivity level ω_{ijt}, so that we can refer to the investment function as $i_{ijt} = i_t(k_{ijt}, l_{ijt}, \omega_{ijt})$. Assuming that investment is strictly monotonic in productivity, we invert the investment function to obtain $\omega_{ijt} = h_t(k_{ijt}, l_{ijt}, i_{ijt})$ and rewrite the regression in (3) as:

$$\tilde{r}_{ijt} = \beta_m \, m_{ijt} + \beta_j \, q_{jt} + \phi_t(k_{ijt}, l_{ijt}, i_{ijt}) + \varepsilon^*_{ijt}, \tag{5}$$

with

$$\phi_t(k_{ijt}, l_{ijt}, i_{ijt}) = \beta_0 + \beta_k \, k_{ijt} + \beta_l \, l_{ijt} + \left(\frac{\sigma_j - 1}{\sigma_j}\right) h_t(k_{ijt}, l_{ijt}, i_{ijt}). \tag{6}$$

Following OP, we approximate the productivity change, $h_t(\cdot)$, with a third-order polynomial in investment, the proxy variable, as well as capital and labor, the state variables. An OLS regression of (5) yields consistent estimates of the coefficients on intermediates which the firm chooses after observing the productivity change as well as the industry's elasticity of substitution. Given the non-parametric treatment of $h_t(\cdot)$, however, both β_k and β_l, remain unidentified in (5).

These coefficients are recovered by exploiting the dynamics of the productivity change as well as information from the firm's exit decision. As in OP, we assume a firm exits the market if its productivity drops below a certain threshold. The value of this threshold depends on the firm's size as measured by its capital stock and level of employment. Firms with larger capital stocks and more trained workers can expect higher returns for any given level of productivity in the future. They will therefore continue to operate at lower productivity levels. Thus, as argued by OP, selection will bias the capital coefficients downwards in an OLS regression of (3). Similarly, a positive productivity change will spur increased use of variable inputs such as intermediates leading to an upward bias on the respective coefficient (β_m) as noted in Van Beveren (2012). In practice, however, the presence of multiple simultaneity issues may undermine any clear prediction of the bias.

To address selection, we introduce an indicator variable, χ_{ijt}, taking zero value if the firms exits in period t and unit value otherwise. As in OP, we fit a probit model of the indicator variable on a second-order polynomial of the first lags of the state and proxy variables to obtain estimates of the probability of survival, $\hat{P}_{ijt}$.

The final step consists of non-parametrically regressing ω_{ijt} on ω_{ijt-1} to obtain coefficient estimates of capital and labor. Given the assumed Markov process, the expected value of the productivity shock, conditional on the firm being active in t can be expressed as $E\left(\omega_{ijt} \,|\, \omega_{ijt-1}, \chi_{ijt} = 1\right) = g\left(P_{ijt}, \omega_{ijt-1}\right)$. We approximate the unknown function $g(\cdot)$ by a second-order polynomial in $\hat{P}_{ijt}$ and $(\hat{\phi}_{t-1} - \beta_k\, k_{ijt-1} - \beta_l\, l_{ijt-1})$. Employing the estimated coefficients on intermediates and industry production from the first stage regression in (5), a consistent estimate of the capital and labor coefficient follows from non-linear regression of:

$$\begin{aligned} \tilde{r}_{ijt} - \hat{\beta}_m\, m_{ijt} - \hat{\beta}_j\, q_{jt} \;&=\; \beta_0 + \beta_k\, k_{ijt} + \beta_l\, l_{ijt} \\ &\quad + g\left(\hat{P}_{ijt},\, \hat{\phi}_{t-1} - \beta_k k_{ijt-1} - \beta_l l_{ijt-1}\right) + \xi_{ijt} + \varepsilon^{*}_{ijt}. \end{aligned} \tag{7}$$

Once all coefficient estimates are retrieved, TFP estimates follow from (4). We obtain standard errors from bootstrapping.

3.4. TFP Estimates for Swiss Manufacturers

The first three columns of Table C.5 present the coefficient estimates following our procedure based on equation (7) and ACF. We estimate the production function without correcting for the omitted price bias to begin with and report the results in the first column. In the second column, we show the results including this correction, assuming a common markup across industries. The third column shows results allowing for industry-specific markups. By analogy, we also report the corresponding coefficient estimates for an OLS fixed-effects regression, OP, and LP.

At first glance, the coefficient estimates turn out to be relatively similar, independent of the estimation algorithm. This assessment is supported by Table C.6. As shown, our TFP estimates prove robust to any of the two-stage algorithms of OP, LP and ACF, given the high correlation of these measures. Confirming our prior of OLS providing biased estimates, we find less correlation between OLS and the two-stage algorithms.

While coefficients on capital are relatively low, in particular—in line with our expectation of a downward bias—for OLS estimates, this result accommodates other empirical studies.[21] As noted in De Loecker (2011), the coefficient on capital measures the elasticity of an input considered to be fixed with respect to the firm's reaction to the contemporaneous productivity shock. We might thus expect the coefficient to be close to zero.

As to the omitted price bias, the coefficient on industry production is statistically significant (with the exception of OLS) which supports our strategy to correct for an omitted price bias. Markups range from a rather timid 5% (LP) to the more reasonable values of 15% (ACF) to 18% (OP) for specifications based on a common elasticity of substitution across industries. Estimates based on industry subsamples such as in Table

[21] For some examples from other small open European economies refer to Van Beveren (2012) and De Loecker (2011) for Belgium, Lööf and Andersson (2010) for Sweden and Görg et al. (2008) for Ireland.

C.7 for the five largest industries (accounting for 75% of total manufacturing sales) suggest somewhat larger markups up to 30% with the implied elasticity of substitutions well in line with benchmark σ's in the literature (e.g. Bernard et al. (2003), Broda and Weinstein (2006)) and close to results reported in comparable regressions (e.g. Ornaghi (2006), De Loecker (2011)).[22]

4. Aggregate Productivity Growth and its Decomposition

With our yearly TFP (and LAP) estimates at the firm level at hand, we now aggregate these values for manufacturing as a whole and then analyze the sources of aggregate productivity growth from 1999 to 2009. We start with aggregate TFP at the manufacturing level and define a firm's sales share, s_{ijt}, as the ratio of its sales, r_{ijt}, to total manufacturing sales, R_t. Denoting the number of firms in industry j by N_{jt}, with the total number of firms equal to $N_t = \sum_{j=1}^{J} N_{jt}$. The shares of all firms in an industry sum up to $S_{jt} = \sum_{i=1}^{N_{jt}} s_{ijt}$ and industry shares accordingly sum up to 1, i.e. $\sum_{j=1}^{J} S_{jt} = \sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} s_{ijt} = 1$. While the sales shares of our sample at the industry level are close to the industry shares published by the SFSO including all firms in the industry (see Table C.3), they do not perfectly match. To ensure that our aggregate results are representative of the Swiss manufacturing sector, we rescale the sample industry shares to match the shares reported by the SFSO in our calculations.[23] We define aggregate TFP at the manufacturing level, Φ_t, as the sales-weighted average of all estimated firm-level TFPs, $\varphi_{ijt} = \exp(\hat{\omega}_{ijt})$:

$$\Phi_t = \sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} s_{ijt}\, \varphi_{ijt}. \tag{8}$$

[22] As outlined in equation 4, the input elasticities follow from multiplying the reported coefficient estimates with the relevant markup, $\sigma_S \,/\, (\sigma_S - 1)$.

[23] Aligning industry shares of the sample to those published for the entire Swiss manufacturing sector primarily reduces the weight of the chemicals industry for the most recent years in our sample. This leads to somewhat lower aggregate TFP and LAP growth, but does not change the qualitative results of our study. The results are available from the authors.

We now decompose aggregate TFP to evaluate different sources of TFP growth. First, we define Φ_t^* as the manufacturing's aggregate TFP, when keeping the industry's sales shares at their initial value in $t = 0$ which corresponds to the year 1999 in our sample:

$$\Phi_t^* = \sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} \frac{S_{j0}}{S_{jt}} s_{ijt} \varphi_{ijt}. \tag{9}$$

The difference between aggregate TFP, Φ_t, and its fixed-industries equivalent, Φ_t^*, is given by (details in appendix Appendix A.1):

$$\Phi_t - \Phi_t^* = \sum_{j=1}^{J} (S_{jt} - S_{j0}) \, \Delta \Phi_{jt}, \tag{10}$$

with $\Delta \Phi_{jt} = \Phi_{jt} - J^{-1} \sum_{j=1}^{J} \Phi_{jt}$ representing the deviation of an industry's aggregate TFP, $\Phi_{jt} = \sum_{i=1}^{N_{jt}} \frac{s_{ijt}}{S_{jt}} \varphi_{ijt}$, from the unweighted mean industry productivity. $\Phi_t - \Phi_t^*$ allows assessing the contribution of inter-industry reallocations to aggregate TFP growth. We can thus detect the aggregate productivity impact of shifts in production to more productive industries. We refer to this as the *inter-industry effect*.

Next, we study the impact of changes in aggregate TFP arising from shifts in market share to more productive firms within industries while controlling for changes in the relative size of the industries. We decompose the fixed-industries TFP, Φ_t^*, into two terms. We refer to the first as the *intra-industry effect* since it accounts for the contribution to aggregate TFP from intra-industry reallocations of sales shares towards firms with above-average productivity. The second term represents the mean of industry TFPs. In both cases sales shares are kept constant at the industry level, to distinguish the impact of intra-industry reallocations on aggregate TFP from inter-industry reallocations accounted for in (10). Specifically, we have (details in appendix Appendix A.2):

$$\Phi_t^* = \underbrace{\sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} S_{j0}\, \Delta s_{ijt} \Delta\varphi_{ijt}}_{\text{intra-industry effect}} + \underbrace{\sum_{j=1}^{J} S_{j0}\, \bar{\varphi}_{jt}}_{\text{mean of industry TFPs}} \quad , \tag{11}$$

defining

$$\Delta s_{ijt} = \frac{s_{ijt}}{S_{jt}} - \frac{1}{N_{jt}} \quad \text{and} \quad \Delta\varphi_{ijt} = \varphi_{ijt} - \bar{\varphi}_{jt}. \tag{12}$$

Δs_{ijt} measures the difference between each firm's sales share within its industry and the unweighted mean sales share (i.e. the inverse of the number of active firms N_{jt}) in the respective industry. By analogy, $\Delta\varphi_{ijt}$ measures the deviation of the firm's TFP from the unweighted mean TFP of the corresponding industry, $\bar{\varphi}_{jt} = (\sum_{i=1}^{N_j t} \varphi_{ijt}) \,/\, N_{jt}$.

The decomposition of TFP in the multi-industry case into an inter- and intra-industry effect refines our understanding of the productivity growth dynamics. That said, these measures can be linked to the decomposition of TFP employed in single-industry analysis such as in OP or more recently Van Beveren (2012). To show this, we subtract the manufacturing sector's unweighted mean TFP , $\bar{\Phi}_t = \left(\sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} \varphi_{ijt}\right) \,/\, N_t$, from the fixed-industries TFP measure, Φ_t^* (details in appendix Appendix A.3):

$$\Phi_t^* - \bar{\Phi}_t = \underbrace{\sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} S_{j0}\, \Delta s_{ijt} \Delta\varphi_{ijt}}_{\text{intra-industry effect}} + \underbrace{\sum_{j=1}^{J} \left(S_{j0} - \bar{S}_{jt}\right) \bar{\varphi}_{jt}}_{\text{deviation in means}}, \tag{13}$$

where $\bar{S}_{jt} = N_{jt} \,/\, N_t$ represents the unweighted mean sales share per industry, i.e. the relative number of firms in the industry. The deviation in means arises from the different weights assigned to industry TFPs. While industry-weights are kept fixed at initial values in Φ_t^*, the unweighted mean $\bar{\Phi}_t$ implicitly weighs industries according to the number of firms active in each industry.

Adding the effect from the reallocation across industries in (10) and within industries as in (13), while accounting for the deviation in means, directly leads to the decomposition of aggregate TFP proposed in OP.

$$\underbrace{\Phi_t \;-\; \Phi_t^*}_{\text{inter-sector}} + (\underbrace{\Phi_t^* \;-\; \bar{\Phi}_t}_{\substack{\text{intra-sector \&} \\ \text{deviation in means}}}) \;=\; \Phi_t \;-\; \bar{\Phi}_t \;=\; \sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} \Delta s_{ijt}^* \, \Delta\varphi_{ijt}^*, \tag{14}$$

where we follow OP in defining $\Delta s_{ijt}^* \;=\; s_{ijt} - \frac{1}{N_t}$ and $\Delta\varphi_{ijt}^* \;=\; \varphi_{ijt} - \bar{\Phi}_t$. The difference Δs_{ijt}^* represents the deviation of the firm's sales share from the average sales share of all firms in the manufacturing sector. By analogy, the term $\Delta\varphi_{ijt}^*$ represents the deviation of the firm's productivity from the unweighted mean productivity in manufacturing, $\bar{\Phi}_t$.

Whereas the sample covariance on the right hand side of (14) allows assessing the share of aggregate productivity growth that can be attributed to a shift of sales in favor of firms with productivity levels above the manufacturing average, we cannot infer whether these reallocations have occurred within or across industries. Since this may be decisive in assessing the impact of, for example, economic policy measures targeting productivity growth, a more informed analysis including the study of both inter- and intra-industry effects is called for. We argue that our decomposition methodology yields crucial insights into the working of industry dynamics. We illustrate this by analyzing productivity growth of Swiss manufacturing in the next section.

5. Results: Productivity Growth in Swiss Manufacturing 1999-2009

In this section we first discuss our results of aggregate TFP of Swiss manufacturing as well as its decomposition according to the methodology proposed in the last section, including an assessment of inter- as well as intra-industry developments. We then turn the focus to developments within single industries.

5.1. Aggregate Productivity Growth

Normalizing aggregate TFP (LAP) to 1 for the year 1999, we highlight the development of the manufacturing sector's TFP (LAP) in the first two columns (labeled "Weighted aggregate") of Table C.8. Our findings suggest a total rise in the sales-weighted aggregate TFP (LAP) of 12% (48%) or an annual growth rate of 1.1% (4.0%) from 1999 to 2009 in the Swiss manufacturing sector. Examining the evolution of LAP a little closer, one observes a peak in 2002 just before the recession. And after the short dip in 2003, LAP continues to grow up to 2009 despite the latest recession. Regarding TFP, we observe a similar peak as in the evolution of LAP just one year later, in 2003. After a not very pronounced fall in 2004, aggregate TFP reaches its maximum in 2007, drops in 2008 and recovers again in the crisis year of 2009. The bold line in Figures D.1 and D.2 display the evolution of aggregate TFP and LAP graphically.

Before examining the observed pattern of aggregate TFP (LAP) using our decomposition and an industry analysis of the productivity estimates, we revert to the TFP (LAP) estimates provided by the EU KLEMS data base (see Table C.10) to provide some guidance on how our figures compare with manufacturing sectors in other advanced economies.[24] Data are available up to the year 2007. Remaining mindful of differences in methodology, we find that Swiss manufacturing is only moderate with an annual growth rate of aggregate TFP of 1.7% which is substantially lower than TFP growth in the US, the UK, but also compared to other small open economies such as Austria and the Netherlands. By contrast, the annual growth rate of LAP in Switzerland of 4.4% compares favorably to other advanced economies, being only outperformed by the US, UK and Austria.

So can policy makers rest comfortable about productivity developments in Swiss manufacturing? To answer this questions we rely on the framework outlined in Section

[24] Switzerland is not included in the KLEMS database. Definitions of the EU KLEMS variables are given in O'Mahony and Timmer (2009). TFP is value-added based. For LAP we selected the volume indices of gross value added per hour worked.

4 that allows looking into the different sources of productivity growth. We focus on the productivity developments for the average firm as well as inter-industry and intra-industry effects (see Table C.8 columns "Unweighted mean", "Inter-industry effect" and "Intra-industry effect", respectively).

5.2. The Decomposition of Productivity Measures

We start with an assessment of developments in the unweighted mean of all manufacturing firms (see Table C.8 column "Unweighted mean"). A first insight is that the means tend to be below the corresponding sales weighted aggregates. Larger firms (in terms of sales shares) are thus, on average, more productive than smaller firms. The difference is less pronounced for TFP, since this measure accounts for the larger firms' greater reliance on capital and intermediates as already highlighted in Table C.4. Strikingly, the evolution of unweighted TFP and LAP over time is substantially less positive than the weighted measures, pointing at an increasing shift of sales shares in favor of more productive firms or industries.

Additionally note that both unweighted mean time series show a similar pattern around the downturn of 2003 with means declining in the run-up to the recession, yet reversing to positive growth during the recession and the year to follow. This pattern is consistent with the exceptionally large productivity gap we find for the firms exiting the market in 2003 and, in particular, 2004. Since these firms typically account for small market shares, their impact on the unweighted means is much stronger than on the sales-weighted productivity aggregates. In difference to this earlier recession, both TFP and LAP means witness an immediate setback during the recession of 2009.

The different evolution of weighted and unweighted TFP (LAP) aggregates implies that major reallocations either across firms or across industries have taken place in the considered period, in the end being responsible for the positive aggregate TFP (LAP) growth in Switzerland. In the last two columns ("Reallocations across firms or industries") of Table C.8 this is illustrated by the generally increasing gap between weighted and unweighted TFP and LAP in the second half of our sample, coming out of the mid-sample recession.

We now turn to the contribution of inter-industry and intra-industry reallocations of sales shares to aggregate productivity growth. As shown in Table C.8 (column "Inter-industry effect") shifts in manufacturing sales towards more productive sectors have increasingly contributed to aggregate LAP growth and to a lesser extent to growth in aggregate TFP. Notably, the year 2009 marks a jump towards more productive sectors expressed by an increase of the inter-industry effect from 0.13 to 0.25 for LAP (0.05 to 0.08 for TFP). Columns labeled "Intra-industry effect" in Table C.8 provide an insight into the importance of the allocation of sales shares towards the most productive firms within industries. A first observation regarding levels adds to our earlier comment, specifying that also within industries large firms differ much more from small firms regarding LAP than TFP. Additionally, values of the intra-industry effect are generally increasing over time, indicating an additional shift to more productive firms within industries in terms of TFP (from 0.05 to 0.19) and LAP (from 0.40 to 0.64). Substantial movements are again observed in 2009, but also between in the run-up and aftermath of the mid-sample recession. The evolution of weighted and unweighted aggregate TFP and LAP as well as the respective reallocations across firms and industries are graphically illustrated in Figures D.1 and D.2.

The absolute magnitude of the inter- and intra-industry-effects may see small. What is of interest, however, is to what extent these effects influence aggregate productivity changes. To this end, we compute the changes of the weighted aggregate as well as of the inter- and intra-industry effects from year to year and plot these changes in Figure D.3 for TFP and Figure D.4 for LAP. In both figures, we observe that changes in the intra-industry effect closely follow changes in the weighted aggregate. The correlation between changes in the inter-industry effect and the weighted aggregate is positive as well, albeit less pronounced. This observation is not too surprising since inter- and intra-industry effect are part of the decomposition of the weighted aggregate by construction. In next step, we thus perform regression decomposition to assess which share of the the variation of the weighted aggregate can be explained by intra- and inter-industry variation. Note that the change in weighted aggregate can be written as

$$\Delta WA = \Delta InterIE + \Delta IntraIE + \Delta UA + \Delta DFM,$$

where WA is the weighted aggregate, $InterIE$ the inter-industry effect, $IntraIE$ the intra-industry effect and DFM the deviation from means as in Tables C.8 and Δ is the year-to-year difference. Regressing each variable from the right-hand side on the change in the weighted aggregate separately, we obtain the share of the variation that this variable contributes to the variation of the weighted aggregate. Table C.12 illustrates that 19.5% of the variation in weighted aggregate TFP can be explained by inter-industry movements while 43.8% are explained by intra-industry reallocations, explaining over 60% of aggregate variation in TFP. Regarding LAP, inter-industry and intra-industry changes even explain all variation in aggregate LAP, the former about one third and the latter roughly two thirds. We conclude that intra- and inter-industry movements determine aggregate productivity changes to a large extent. In the case of Swiss manufacturing, the latter effect is about twice as important than the former.

5.3. The Exceptional Performance of the Chemical and Pharmaceutical Industry

Summarizing the previous discussion, we observe that the productivity growth observed in Switzerland is due to both, an inter-industry and an intra-industry effect. It is also remarkable that some of the largest reallocations are observed in the crisis year of 2009. This is all the more interesting in the light of our results that suggest substantial productivity increases in this year of economic turmoil, an observation that requires further explanation. We hence investigate TFP and LAP growth in the different manufacturing industries in Switzerland. Table C.11 displays growth rates of TFP (LAP) of 13 different industries. The chemicals industry stands tall with a growth rate of TFP (LAP) of 71% (82%)—an annual growth rate of 5.5% (6.1%)—between 1999 and 2009 as displayed in the fifth (tenth) column of the table. Overall, only two (six) out of 13 industries exhibit positive growth rates over the full period. Strikingly, the chemicals industry also exhibited an above-average productivity growth of 15% (8%) during the 2009 recession. Excluding the chemicals industry from our sample as shown in the last row of the table, we measure an aggregate productivity drop between 1999 and 2009 of 11% (4%) instead of the above-mentioned substantial increase of 12% (48%) including this industry. Also, we observe a severe drop in productivity levels in the 2009 recession by 8% (12%) when excluding chemical and pharmaceutical products.

Hence, the growth in productivity observed at the aggregate level of Swiss manufacturing is almost solely driven by the chemicals industry which is on average responsible for one fifth of sales in Swiss manufacturing. It is now of interest whether the reallocations observed in Table C.8 were also driven by the dominant chemicals industry. We analyze this by performing the decomposition of TFP (LAP) again, this time without including this industry. Considering the first two columns of Table C.9, we first observe that aggregate TFP remains relatively closely around the level of 1999 until 2008 and then drops substantially in 2009 while LAP initially increases after its 2004 slump and then drops below the level of 1999 in 2009.

Two further observations stand out: First, inter-industry shifts towards the chemicals industry seem to account for the entire inter-industry effect observed in Table C.8 as they vanish almost completely in Table C.9 regarding both, TFP and LAP. Second, the values depicting the intra-industry effect are still positive, expressing that larger firms are still more productive. However, these values are not larger at the of the observed period. Hence, we do not observe additional shifts towards more productive firms within industries once excluding the chemicals industry. Some shifts towards more productive firms are observed during the 2003 recession. However, these reallocations are undone in the aftermath of the recession.

As mentioned in the introduction of this paper, the chemicals and pharmaceuticals industry has been emphasized by others to be one of the exceptional examples of Swiss industries that showed high growth rates of LAP in the last decades of the 20th century. Our analysis fully supports this view, raising the question of what has driven this development.

5.4. Industry Responses to a Changing Economic Environment

Industries have responded differently to the economic downturns of 2003 and 2009, with Swiss annual GDP slipping by 0.2% and 1.9% respectively. In both cases, the downturn was only short-lived with economic activity picking up strongly in the year following the recession. The 2009 recession, however, was marked by an unprecedented decline in Swiss exports and imports and is thus likely to have affected industries quite differently than in 2003, when trading activity remained at par with the year before. As noted when discussing the results in Tables C.8 and C.9, the recessions are visible in both the aggregate productivity measures as well as their components. The impact of the 2003 recession, however, seems to have played out not before the year 2004, while the downturn in 2009 immediately affected firms' productivity and market share allocation. Accordingly, we highlight the year-on-year changes in TFP and LAP from 2003 to 2004 and from 2008 to 2009 in Table C.11. Looking at the total impact displayed in the last two rows of Table C.11 supports our initial view that the downturn in 2009 has had a much severe impact on firms than the preceding recession. Much different to 2003/04, the later recession depressed LAP in nearly all industries, with chemicals, computer manufacturers and metal products being the only exception. As noted earlier, the resilience in LAP observed in the chemicals industry rests, in part, on shifts in sales towards the industry's most productive firms. Developments in TFP are less conclusive during 2009, with growth the transport equipment industry standing out. Given the limited amount of observations per industry, however, an interpretation of single year developments needs to remain mindful of the impact of firm entry and exits from the sample.

Given the period of observation in our sample, an imminent question is whether increasing integration with the EU has been a driving factor of the productivity change over time. Note that approximately 80% of Swiss imports in goods and services originate from the EU, whereas 60% of the Swiss exports go into the EU. In 1999, Switzerland signed a first set of bilateral agreements with the EU, including most notably provisions for the free movement of persons. These agreements came into effect in June 2002, although the free movement of persons was effectively phased-in over several years for EU member states joining the union after 2002. At first glance, enforcement of the bilateral agreements coincides with the rise in TFP (and to a smaller extent of LAP) in 2003 and thereafter discussed above. In a study of the impact of trade liberalization with the EU on plant-level growth in Switzerland Buehler et al. (2011) categorize industries according to how strong they have been affected by these bilateral agreements. According to these authors plants in industries affected more strongly by the bilateral trade liberalization grew faster in the six years following 2002.[25] Employing the same categorization, we consider industries 9 to 12 the most affected by the bilateral trade liberalization. As an initial assessment, we find considerable growth in employment in these industries—the productivity measure Buehler et al. (2011) rely on— as well as a sizeable pick-up in LAP growth with the exception of transport equipment. Conversely, our data do not confirm that these industries have generally outperformed others in terms of TFP growth since the bilateral agreements have come into effect.

[25] Buehler et al. (2011) measure plant growth in terms of employment growth due to data limitations.

6. Conclusion

This paper estimates the development of TFP at the firm-level for nearly 2,000 Swiss manufacturing firms. Our results are based on a novel data set covering the years from 1997 to 2009. We employ a two-stage estimation procedure following Ackerberg et al. (2006) to yield consistent estimates of TFP. We also correct for possible omitted price biases due to Klette and Griliches (1996) and De Loecker (2011). Moreover, we propose a framework to decompose aggregate productivity changes into inter-industry and intra-industry effects. We check the robustness of our production function estimates by reference to a number of alternative specifications and that the time series for TFP does not reveal any contradiction to that for the simply calculated labor productivity (LAP) measures.

Our findings suggest that aggregate LAP growth in the Swiss manufacturing sector has been surprisingly high from 1999 to 2009 if compared to other studies with estimates of approximately 1% in terms of LAP for the 1980s and 1990s for the Swiss economy as a whole. We find that productivity in Swiss manufacturing rose by an average yearly growth rate of 4% for LAP. By contrast, aggregate TFP growth stands at only 1% per year on average. The cornerstone of the productivity growth has been the chemicals industry (including pharmaceuticals and petroleum products) supporting other studies on this subject. The chemicals industry has witnessed a strong shift of production towards the most productive firms with considerable productivity gains at large firms. Most other industries report an overall decline in productivity with estimates varying markedly across industries and over time. These findings point to policy challenges regarding the cross-industry effectiveness of growth promoting policy measures.

Our decomposition of the change of productivity of the Swiss manufacturing sector reveals that intra- and inter-industry effects can explain a significant share of productivity growth. Yet, specialization into more productive industries as well as reallocation within industries has been dominated by developments in the chemicals industry. Leaving this industry aside, the Swiss manufacturing sector shows surprisingly little inter- or intra-sector dynamics.

TFP is widely considered a good indication of a firm's or industry's performance and a better measure of productivity than LAP. Our study is thus a first step in analyzing the details of aggregate productivity for the Swiss manufacturing sector. In future work, it would be interesting to investigate the determinants of these productivity changes. For example, given the Swiss economy's openness, a key dimension to look at is the firms' international activities. It is definitely not by coincidence, that the chemicals industry is marked by strong TFP growth and, in addition, is known to having contributed most to Switzerland's export growth during the same period. Additional information on the firms' importing and exporting activities would thus complement our analysis of the driving forces of productivity growth.

Other work left for future research is linked to our findings regarding the decomposition of the sources of productivity growth. Our result for the Swiss manufacturing sector as a whole can be interpreted that resources are shifted to more productive firms away from less productive firms. This is the emphasis of the new trade literature based on firm heterogeneity. However, the result may also be regarded as compatible with traditional trade theory as specialization towards more productive industries proves to be an essential source of productivity growth in our analysis. In order to discriminate between the two views more has to be done and known on the dynamics of exit, entry and expansion of individual firms.

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Appendix A. Derivations

Appendix A.1. Details to deriving the inter-industry effect in (10)

Our second TFP measure, Φ_t^*, is based on keeping industry shares fixed at their initial value in $t = 0$. This requires rescaling the firms' shares in $t > 0$ so that:

$$\Phi_t^* = \sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} \frac{S_{j0}}{S_{jt}} s_{ijt} \varphi_{ijt} \tag{A.1}$$

The difference between aggregate TFP and its fixed-industries equivalent accounts for the contribution of inter-industry reallocations to aggregate TFP growth:

$$\begin{aligned}
\Phi_t - \Phi_t^* &= \left(\sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} s_{ijt} \varphi_{ijt} \right) - \left(\sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} \frac{S_{j0}}{S_{jt}} s_{ijt} \varphi_{ijt} \right) \\
&= \sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} (S_{jt} - S_{j0}) \frac{s_{ijt}}{S_{jt}} \varphi_{ijt} \\
&= \sum_{j=1}^{J} (S_{jt} - S_{j0}) \sum_{i=1}^{N_{jt}} \frac{s_{ijt}}{S_{jt}} \varphi_{ijt} \\
&= \sum_{j=1}^{J} (S_{jt} - S_{j0}) \Phi_{jt} = \sum_{j=1}^{J} (S_{jt} - S_{j0}) \Delta \Phi_{jt}
\end{aligned} \tag{A.2}$$

where $\Phi_{jt} = \sum_{i=1}^{N_{jt}} \frac{s_{ijt}}{S_{jt}} \varphi_{ijt}$ is the industry equivalent of aggregate TFP, Φ_t, since s_{ijt} / S_{jt} corresponds to each firm's sales share within its industry. $\Delta \Phi_{jt}$ represents the difference between Φ_{jt} and the unweighted mean of the industries' TFPs, $\bar{\Phi}_{jt} = J^{-1} \sum_{j=1}^{J} \Phi_{jt}$. Note that the result in the last line of (A.2) follows from

$$\sum_{j=1}^{J} (S_{jt} - S_{j0}) \bar{\Phi}_{jt} = \bar{\Phi}_{jt} \sum_{j=1}^{J} (S_{jt} - S_{j0}) = 0. \tag{A.3}$$

Appendix A.2. Details to deriving the intra-industry effect in (11)

Based on the definitions of $\Delta s_{ijt} = \frac{s_{ijt}}{S_{jt}} - \frac{1}{N_{jt}}$ and $\Delta\varphi_{ijt} = \varphi_{ijt} - \bar{\varphi}_{jt}$ provided in (12) we write Φ_t^* as

$$\begin{aligned}
\Phi_t^* &= \sum_{j=1}^{J}\sum_{i=1}^{N_{jt}} S_{j0}\left(\Delta s_{ijt} + \frac{1}{N_{jt}}\right)(\Delta\varphi_{ijt} + \bar{\varphi}_{jt}) \\
&= \left(\sum_{j=1}^{J}\sum_{i=1}^{N_{jt}} S_{j0}\,\Delta s_{ijt}\Delta\varphi_{ijt}\right) + \left(\sum_{j=1}^{J}\sum_{i=1}^{N_{jt}} \frac{S_{j0}}{N_{jt}}\,\bar{\varphi}_{jt}\right) \\
&= \left(\sum_{j=1}^{J}\sum_{i=1}^{N_{jt}} S_{j0}\,\Delta s_{ijt}\Delta\varphi_{ijt}\right) + \left(\sum_{j=1}^{J} \frac{S_{j0}}{N_{jt}}\,N_{jt}\,\bar{\varphi}_{jt}\right) \\
&= \left(\sum_{j=1}^{J}\sum_{i=1}^{N_{jt}} S_{j0}\,\Delta s_{ijt}\Delta\varphi_{ijt}\right) + \left(\sum_{j=1}^{J} S_{j0}\,\bar{\varphi}_{jt}\right) \qquad \text{(A.4)}
\end{aligned}$$

In the above derivation we make use of the fact that the following sums have zero value:

$$\sum_{j=1}^{J}\sum_{i=1}^{N_{jt}} \frac{S_{j0}}{N_{jt}}\,\Delta\varphi_{ijt} = \sum_{j=1}^{J}\frac{S_{j0}}{N_{jt}}\underbrace{\sum_{i=1}^{N_{jt}}\Delta\varphi_{ijt}}_{=0} = 0$$

$$\sum_{j=1}^{J}\sum_{i=1}^{N_{jt}} S_{j0}\,\Delta s_{ijt}\,\bar{\varphi}_{jt} = \sum_{j=1}^{J} S_{j0}\,\bar{\varphi}_{jt}\underbrace{\sum_{i=1}^{N_{jt}}\Delta s_{ijt}}_{=0} = 0$$

Appendix A.3. Details to deriving $\Phi_t^* - \bar{\Phi}_t$ *in* (13)

Subtracting the manufacturing sector's unweighted mean TFP, defined as $\bar{\Phi}_t = \left(\sum_{j=1}^{J}\sum_{i=1}^{N_{jt}}\varphi_{ijt}\right)/N_t$, from the fixed-industries TFP measure, Φ_t^*, yields:

$$
\begin{aligned}
\Phi_t^* - \bar{\Phi}_t &= \left(\sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} S_{j0}\, \Delta s_{ijt} \Delta\varphi_{ijt} \right) + \left(\sum_{j=1}^{J} S_{j0}\, \bar{\varphi}_{jt} \right) - \frac{1}{N_t} \sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} \varphi_{ijt} \\
&= \left(\sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} S_{j0}\, \Delta s_{ijt} \Delta\varphi_{ijt} \right) + \left(\sum_{j=1}^{J} S_{j0}\, \bar{\varphi}_{jt} \right) - \frac{1}{N_t} \sum_{j=1}^{J} \bar{\varphi}_{jt}\, N_{jt} \\
&= \left(\sum_{j=1}^{J} \sum_{i=1}^{N_{jt}} S_{j0}\, \Delta s_{ijt} \Delta\varphi_{ijt} \right) + \left(\sum_{j=1}^{J} \left(S_{j0} - \bar{S}_{jt} \right) \bar{\varphi}_{jt} \right) \qquad \text{(A.5)}
\end{aligned}
$$

where $\bar{S}_{jt} = N_{jt} / N_t$.

Appendix B. Data

Data are obtained from the Swiss Federal Statistical Office (SFSO) under strict confidentiality requirements. The following tables list the used variables from balance-sheet data as well as the deflators employed to obtain real values. Deflators are obtained from either the SFSO, the OECD, or the Swiss Federal Customs Administration. Aggregate industry statistics, as for example industry production, total number of firms per industry or total employment are obtained from official SFSO statistics.

Table B.1: Balance-sheet variables obtained from Swiss Federal Statistical Office

Variable name	Description
employment	Employees, full-time equivalents
revenue	Revenue
labor_exp	Labor expenditures (wages, social security, etc. included)
mat_exp	Material expenditures
cap_stock	Capital stock (movables and machinery)
depreciation	Depreciation of movables and machinery

From these data we obtain the variables used in the descriptive analysis as well as in the estimation of productivity measures. The average wage is obtained by dividing all labor expenditures of firms (including social security expenses, etc.) by full-time equivalent employment. Intermediates per employee are derived in the same fashion.

The capital stock is based on balance sheet information on movables and machinery and capital per employee is again derived by dividing by full-time equivalents. The investment variable used for the estimation of the production function composed of information on annual depreciation as well as on the change of the capital stock. In the estimation of the production function, investment, capital stock and intermediate expenditures are deflated to obtain real values. Full-time equivalents are used to proxy real labor input. Labor productivity is defined as real revenue divided by the number of employee full-time equivalents.

Table B.2: Deflators

Deflator name	Description
revenue_defl_bfs	Deflates revenue based on BFS revenue indices
mat_exp_defl_oecd	Deflates material expenditures based on OECD int. input indices
labor_exp_defl_bfs	Deflates labor expenditures based on BFS wage indices
inv_defl_ezv	Deflates investment goods based on EZV import indices
cap_stock_defl_ezv	Deflates investment goods based on EZV import indices

Appendix C. Tables

Table C.3: Industry definition and sample coverage

			Sale shares		Coverage	
	NOGA*	Industry definition	Sample**	SFSO**	Sales**	Firms***
1	15-16	Beverages, food and tobacco products	14%	11%	71%	7%
2	17-19	Textiles, apparel and leather products	2%	2%	61%	7%
3	20-21	Wood and paper products, cork and pulp	4%	5%	43%	2%
4	22	Publishing and printing	4%	5%	49%	3%
5	23-24	Chemical products, pharmaceutical products	21%	21%	56%	14%
6	25-26	Rubber, plastic and other non-metallic products	5%	5%	54%	10%
7	27	Basic metals	3%	2%	77%	24%
8	28	Metal products	4%	8%	32%	3%
9	29	Machinery and equipment	15%	14%	58%	6%
10	30-32	Computers, electrical machinery, communication equipment	12%	9%	77%	12%
11	33	Medical, precision and optical instruments	12%	12%	59%	4%
12	34-35	Transport equipment	2%	2%	49%	9%
13	36	Furniture	2%	3%	31%	2%

* Swiss industry classification (NOGA 2002) at the 2-digit level. Corresponds to ISIC 3.1.
** Mean values, 1997-2009.
*** Values from 2008

Table C.4: Firm size and characteristics

	1997		2001		2005		2009	
Number of firms								
$L < 50$	445	25%	462	24%	626	32%	395	24%
$50 \geq L < 100$	525	30%	569	29%	489	25%	472	28%
$100 \geq L < 200$	427	24%	476	25%	432	22%	402	24%
$200 \geq L < 500$	251	14%	308	16%	300	15%	275	17%
$L > 500$	106	6%	116	6%	108	6%	113	7%
All	1754	100%	1931	100%	1955	100%	1657	100%
Average wage								
$L < 50$	73	-5%	79	-5%	84	-5%	89	-4%
$50 \geq L < 100$	76	-1%	82	-2%	87	-2%	91	-2%
$100 \geq L < 200$	78	0%	83	0%	90	1%	93	0%
$200 \geq L < 500$	81	5%	87	5%	94	6%	96	3%
$L > 500$	90	16%	96	14%	106	19%	109	17%
All	77	-	83	-	89	-	93	-
Capital per employee								
$L < 50$	18	-11%	19	-19%	17	-26%	22	-21%
$50 \geq L < 100$	20	-4%	20	-14%	22	-3%	23	-17%
$100 \geq L < 200$	22	6%	24	2%	24	6%	26	-5%
$200 \geq L < 500$	23	9%	33	42%	28	24%	39	41%
$L > 500$	24	17%	29	26%	39	71%	44	60%
All	21	-	23	-	23	-	27	-
Intermediates per employee								
$L < 50$	115	-13%	127	-11%	138	-12%	155	1%
$50 \geq L < 100$	125	-5%	133	-7%	146	-7%	129	-16%
$100 \geq L < 200$	138	5%	145	1%	167	6%	146	-5%
$200 \geq L < 500$	142	8%	165	16%	168	7%	175	14%
$L > 500$	189	43%	191	33%	256	62%	228	49%
All	132	-	143	-	158	-	153	-
Labor productivity								
$L < 50$	239	-11%	260	-12%	277	-14%	309	-5%
$50 \geq L < 100$	256	-5%	275	-7%	302	-6%	278	-14%
$100 \geq L < 200$	284	5%	300	1%	337	5%	319	-1%
$200 \geq L < 500$	294	9%	346	17%	359	12%	363	12%
$L > 500$	360	33%	390	32%	509	58%	488	51%
All	270	-	296	-	322	-	324	-

Notes: L is equal to the number of employees in terms of full-time equivalents. The percentages in the number-of-firms-panel express the relative shares. The percentages in the other panels express the relative deviation from the total manufacturing average. In these panels, numbers are in 1'000 Swiss Francs.

Table C.5: Production function estimates

	ACF			OLS		
Labor	0.485***	0.499***	0.514***	0.521***	0.526***	0.538***
	(0.006)	(0.006)	(0.005)	(0.024)	(0.024)	(0.023)
Capital	0.068***	0.058***	0.039***	0.007**	0.008**	0.007**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Intermediates	0.468***	0.438***	0.481***	0.348***	0.349***	0.350***
	(0.003)	(0.003)	(0.003)	(0.021)	(0.021)	(0.021)
Industry Production		0.154***			-0.080***	
		(0.003)			(0.020)	
N	17263	17263	17263	22627	22627	22627

	OP			LP		
Labor	0.514***	0.485***	0.545***	0.455***	0.450***	0.478***
	(0.006)	(0.006)	(0.006)	(0.012)	(0.018)	(0.016)
Capital	0.052***	0.075***	0.021***	0.066***	0.064***	0.037***
	(0.002)	(0.001)	(0.002)	(0.017)	(0.017)	(0.010)
Intermediates	0.484***	0.443***	0.497***	0.464***	0.461***	0.493***
	(0.003)	(0.003)	(0.003)	(0.082)	(0.071)	(0.060)
Industry Production		0.176***			0.054***	
		(0.003)			(0.007)	
N	17263	17263	17263	22627	22627	22627

Notes: * p<0.1, ** p<0.05, *** p<0.01. ISD: Regression with industry-specific dummies.

Table C.6: Correlation across different estimates of firm-level TFP

	ACF	OLS	OP	LP
ACF	1			
OLS	0.7279	1		
OP	0.9964	0.6727	1	
LP	0.9684	0.8309	0.9522	1

Notes: Correlation of all firm's TFP estimates across different estimation strategies.

Table C.7: Production function estimates for the five largest industries

	1	5	9	10	11
Industry	Food	Chemicals	Machinery	Computers	Prec. instr.
Labor	0.455***	0.506***	0.583***	0.506***	0.428***
	(0.033)	(0.018)	(0.032)	(0.051)	(0.028)
Capital	0.054***	0.085***	-0.006	-0.004	0.071***
	(0.010)	(0.012)	(0.008)	(0.017)	(0.012)
Intermediates	0.501***	0.437***	0.530***	0.436***	0.471***
	(0.006)	(0.012)	(0.007)	(0.010)	(0.008)
Industry Production	0.238***	0.275***	0.226***	0.309***	0.229***
	(0.011)	(0.018)	(0.009)	(0.015)	(0.015)
N	1473	958	2142	1689	1436
Avg. revenue share	14%	21%	15%	12%	12%

Notes: * p<0.1, ** p<0.05, *** p<0.01. Industry 1: Beverages, food and tobacco products; Industry 5: Chemical products, pharmaceuticals; Industry 9: Machinery and equipment; Industry 10: Computers, electrical machinery, comm. equipment; Industry 11: Medical, precision and optical instruments. ACF estimates.

Table C.8: Decomposition of aggregate TFP and LAP (all industries)

	Weighted aggregate		Unweighted mean		Inter-industry effect		Intra-industry effect		Deviation from mean		Reallocations across firms and industries	
Year	TFP	LAP	TFP	LAP	TFP	LAP	TFP	LAP	TFP	LAP	TFP	LAP
1999	1.00	1.00	0.96	0.51	0.00	0.00	0.05	0.40	-0.01	0.09	0.04	0.49
2000	1.00	1.07	0.96	0.54	0.00	0.01	0.05	0.42	-0.02	0.09	0.04	0.52
2001	0.97	1.06	0.92	0.53	0.00	0.03	0.07	0.42	-0.03	0.08	0.04	0.53
2002	0.97	1.25	0.89	0.51	-0.01	0.10	0.12	0.56	-0.03	0.09	0.08	0.74
2003	1.09	1.19	0.94	0.53	0.01	0.09	0.16	0.48	-0.02	0.09	0.15	0.66
2004	1.03	1.16	1.01	0.55	0.02	0.10	0.08	0.42	-0.07	0.09	0.02	0.61
2005	1.06	1.25	1.02	0.57	0.02	0.12	0.09	0.47	-0.08	0.09	0.03	0.67
2006	1.12	1.38	1.01	0.59	0.05	0.14	0.13	0.56	-0.07	0.09	0.11	0.79
2007	1.15	1.41	1.00	0.61	0.05	0.12	0.15	0.56	-0.05	0.11	0.15	0.79
2008	1.10	1.43	0.94	0.62	0.05	0.13	0.16	0.55	-0.05	0.13	0.16	0.81
2009	1.12	1.48	0.89	0.53	0.08	0.25	0.19	0.64	-0.05	0.06	0.23	0.95

TFP: ACF.

Table C.9: Decomposition of aggregate TFP and LAP (except chemicals)

	Weighted aggregate		Unweighted mean		Inter-industry effect		Intra-industry effect		Deviation from mean		Reallocations across firms and industries	
Year	TFP	LAP	TFP	LAP	TFP	LAP	TFP	LAP	TFP	LAP	TFP	LAP
1999	1.00	1.00	0.97	0.61	0.00	0.00	0.05	0.35	-0.02	0.04	0.03	0.39
2000	1.04	1.06	0.97	0.65	0.01	0.00	0.08	0.38	-0.01	0.03	0.07	0.41
2001	1.00	0.99	0.94	0.61	0.00	0.01	0.09	0.35	-0.03	0.02	0.07	0.38
2002	1.01	0.96	0.91	0.58	-0.01	0.00	0.14	0.36	-0.03	0.02	0.10	0.38
2003	1.06	0.98	0.94	0.61	0.00	0.01	0.15	0.34	-0.04	0.02	0.12	0.37
2004	1.00	0.94	1.02	0.64	0.01	0.00	0.07	0.28	-0.10	0.02	-0.02	0.30
2005	1.02	1.06	1.03	0.67	0.01	0.02	0.07	0.35	-0.10	0.02	-0.02	0.39
2006	1.01	1.13	1.02	0.69	0.02	0.02	0.05	0.39	-0.09	0.02	-0.02	0.44
2007	1.00	1.12	1.00	0.71	0.02	0.01	0.07	0.38	-0.09	0.02	-0.01	0.41
2008	0.97	1.12	0.94	0.69	0.03	0.02	0.08	0.38	-0.08	0.03	0.03	0.43
2009	0.89	0.96	0.90	0.60	0.01	0.03	0.06	0.32	-0.07	0.00	0.00	0.35

TFP: ACF.

Table C.10: Average annual growth rates in manufacturing sector

	1999-2007	
	TFP	LAP
US	3.7%	5.3%
Austria	3.7%	4.4%
UK	3.2%	4.7%
Germany	2.8%	3.7%
The Netherlands	2.5%	3.7%
Switzerland	1.8%	4.4%
France	1.7%	3.3%
Japan	1.2%	4.1%
Spain	-0.1%	1.5%
Italy	-0.1%	0.7%

Notes: (*) Values for 1999 to 2006 only. Source: EU KLEMS data base for all countries except for Switzerland.

Table C.11: Relative Changes of TFP and LAP

		Total factor productivity					Labor productivity				
	Industry	99-03	*03-04*	04-08	*08-09*	**99-09**	99-03	*03-04*	04-08	*08-09*	**99-09**
1	Beverages, food and tobacco products	-8%	*0%*	0%	*-4%*	**-11%**	-10%	*3%*	17%	*-13%*	**-6%**
2	Textiles, apparel and leather products	-10%	*12%*	15%	*-8%*	**7%**	-13%	*17%*	31%	*-16%*	**11%**
3	Wood and paper products, cork and pulp	-7%	*3%*	-6%	*-4%*	**-12%**	-4%	*3%*	7%	*-13%*	**-7%**
4	Publishing and printing	-42%	*47%*	3%	*-25%*	**-34%**	-14%	*11%*	4%	*-14%*	**-14%**
5	Chemical products, pharmaceutical products	20%	*-6%*	31%	*15%*	**71%**	35%	*-3%*	29%	*8%*	**82%**
6	Rubber, plastic, other non-metallic prod.	19%	*8%*	-10%	*-14%*	**-1%**	32%	*11%*	7%	*-14%*	**36%**
7	Basic metals	21%	*-7%*	-22%	*-3%*	**-14%**	-18%	*23%*	7%	*-31%*	**-26%**
8	Metal products	11%	*-4%*	-20%	*10%*	**-6%**	9%	*-1%*	-7%	*0%*	**1%**
9	Machinery and equipment	-3%	*0%*	1%	*-3%*	**-5%**	4%	*4%*	38%	*-30%*	**5%**
10	Computers, electrical machinery, comm. eq.	18%	*-16%*	0%	*-10%*	**-10%**	3%	*-10%*	20%	*5%*	**17%**
11	Medical, precision and optical instr.	9%	*-25%*	10%	*-22%*	**-29%**	-10%	*-29%*	25%	*-24%*	**-39%**
12	Transport equipment	-6%	*9%*	-17%	*-8%*	**-21%**	-4%	*9%*	1%	*-11%*	**-5%**
13	Furniture	-5%	*-7%*	-1%	*-4%*	**-15%**	-7%	*-17%*	21%	*-15%*	**-20%**
	Total	9%	*-6%*	6%	*2%*	**12%**	19%	*-3%*	24%	*4%*	**48%**
	Total, excluding chemicals industry (5)	6%	*-6%*	-3%	*-8%*	**-11%**	-2%	*-4%*	19%	*-15%*	**-4%**

Table C.12: Regression decomposition of aggregate productivity changes

	TFP	LAP
Δ inter-industry effect	0.195**	0.319**
	(0.078)	(0.135)
Δ intra-industry effect	0.438**	0.703***
	(0.175)	(0.109)
Δ unweighted mean	0.152	-0.025
	(0.246)	(0.126)
Δ deviation from mean	0.215*	0.003
	(0.107)	(0.104)

Appendix D. Figures

Figure D.1: Aggregate TFP

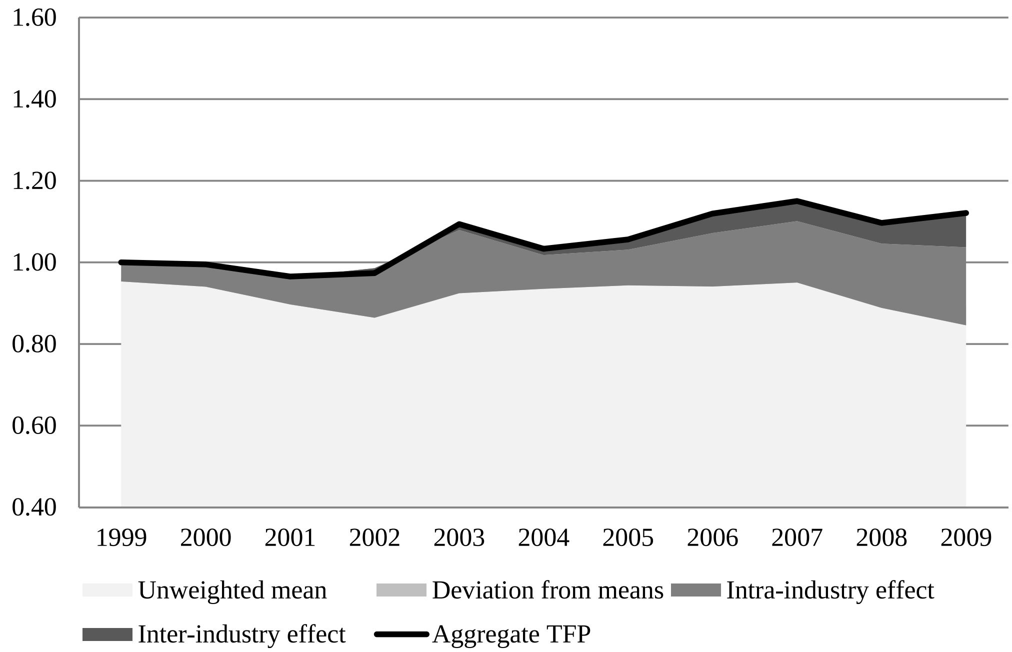

Figure D.2: Aggregate LAP

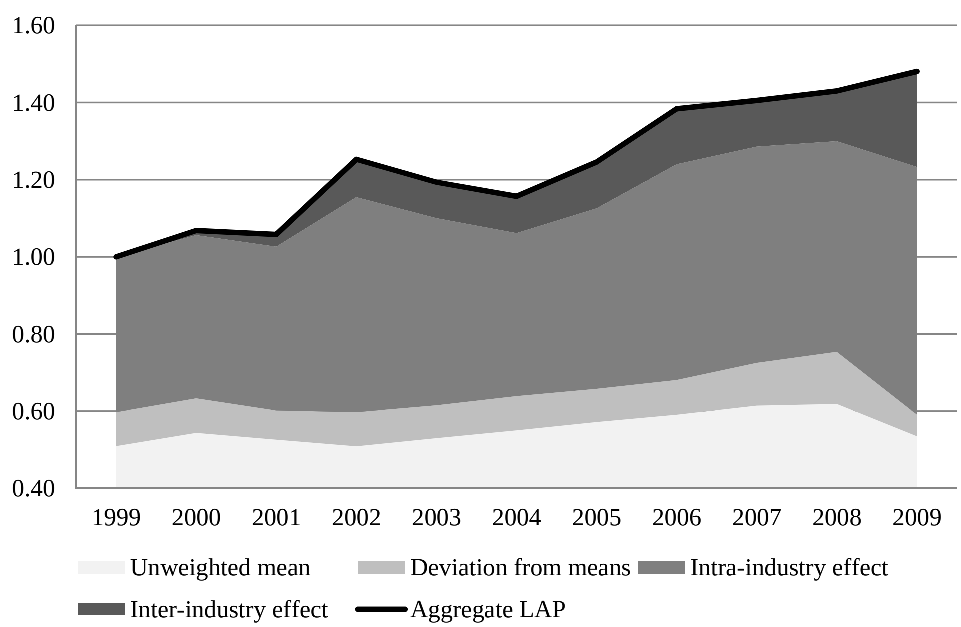

Figure D.3: Explaining Differences in TFP over Time

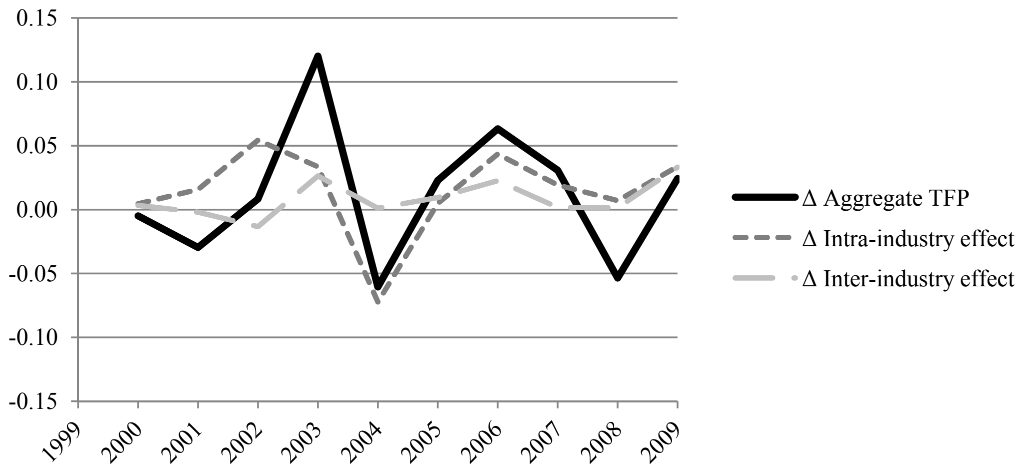

Figure D.4: Explaining Differences in LAP over Time