UNIVERSITÉ DE NEUCHÂTEL

FACULTÉ DES SCIENCES ÉCONOMIQUES

Four Empirical Essays on Agglomeration Economies and Firm-level Productivity Performance in Switzerland

PhD thesis submitted to the Faculty of Economics and Business

Institute of Economic Research

University of Neuchâtel

For the PhD degree in Economics

by

Benjamin TISSOT-DAGUETTE

Approved by the dissertation committee:

Jean-Marie GRETHER, PhD, Professor, University of Neuchâtel, thesis director

Daniel KAUFMANN, PhD, Assistant Professor, University of Neuchâtel, president of the committee

Tobias MÜLLER, PhD, Professor, University of Geneva

Claudio SFREDDO, PhD, Ecole hôtelière de Lausanne, University of Applied Sciences and Arts Western Switzlerand (HES-SO)

Defended on September 10th, 2019

UNIVERSITÉ DE
NEUCHÂTEL

IMPRIMATUR POUR LA THÈSE

Four Empirical Essays on Agglomeration Economies and Firm-level Productivity Performance in Switzerland

Benjamin TISSOT-DAGUETTE

UNIVERSITÉ DE NEUCHÂTEL

FACULTÉ DES SCIENCES ÉCONOMIQUES

La Faculté des sciences économiques,
sur le rapport des membres du jury

Prof. Jean-Marie Grether (directeur de thèse, Université de Neuchâtel)
Prof. Daniel Kaufmann (président du jury, Université de Neuchâtel)
Prof. Tobias Müller (Université de Genève)
Dr. Claudio Sfreddo (Ecole hôtelière de Lausanne and
University of Applied Sciences and Arts Western Switzerland HES-SO)

Autorise l'impression de la présente thèse.

Neuchâtel, le 23 septembre 2019

Annik Dubied

La doyenne
Annik Dubied

Abstract

This thesis explores empirically the Swiss economic productive structure from three different angles. First, it applies multiple imputation techniques to combine existing data sources and to construct new and representative value-added databases at the firm level. These finely disaggregated databases are used to explore regional productivity patterns in Switzerland applying a novel decomposition derived from the shift-share literature. This analysis progressively "zooms" into the Swiss industrial and geographical landscape unveiling the competitive and structural effects which underpin the very low Swiss productivity growth of the last decades. Second, relying on firms creation data sources, the thesis estimates the magnitude of the different types of agglomeration forces at work in Switzerland. Third, the thesis scrutinizes the spatial mismatch between income and production, as the most productive Swiss regions are not necessarily the ones reporting the largest revenues. The results obtained from these three complementary perspectives should be of interest to assess Swiss industrial and spatial development policies, as well as to inform the fiscal equalization and geographical equity debates across Swiss municipalities.

Keywords: Swiss firms, value-added, agglomeration economies, productivity growth, shift-share, structural and competitive effects, localization elasticities, urbanization elasticities, firms creation, income, spatial, mismatch, distribution.

Résumé

Cette thèse explore empiriquement le paysage économique suisse de trois perspectives. Premièrement, en appliquant des techniques d'imputation multiple et en combinant des sources de données existantes, elle décrit la création de nouvelles bases de données représentatives de la valeur ajoutée au niveau de la firme. Ces bases de données désagrégées sont utilisées pour explorer la distribution de la productivité des régions suisses à l'aide d'une nouvelle méthode de décomposition inspirée de la littérature "shift-share". Cette analyse "zoome" progressivement dans le paysage industriel et géographique suisse dévoilant les effets structuraux et compétitifs qui sous-tendent la très faible croissance des dernières décennies de la productivité en Suisse. Deuxièmement, en se basant sur des données portant sur la création de nouvelles firmes, cette thèse estime la magnitude des différentes forces d'agglomération en Suisse. Troisièmement, comme les régions suisses les plus productives ne sont pas forcément celles qui comptabilisent le plus de revenu, cette thèse examine l'inadéquation spatiale entre revenu et production. Les résultats obtenus par ces trois perspectives complémentaires sont d'intérêt pour le développement des politiques industrielles et d'aménagement du territoire suisses, ainsi que pour nourrir les débats sur la péréquation financière et l'équité spatiale entre communes suisses.

Mots-clefs: firmes suisses, valeur ajoutée, économies d'agglomération, croissance de la productivité, shift-share, effets structuraux et compétitifs, élasticités de localisation, élasticités d'urbanisation, création de firmes, revenus, analyse spatiale, inadéquation, distribution.

Short Contents

Contents

List of Figures

List of Tables

Acknowledgments

First of all, I would like to thank my supervisor Jean-Marie Grether. Brilliant researcher and teacher, he guided me and helped me tremendously during these five years of PhD. Despite of a very busy agenda, he was always ready to meet to talk about research or teaching. I highly appreciated collaborating with him. I also enjoyed supporting him in his teaching activities, notably in the macroeconomics class together with Luciano. But what impressed me the most about JMG was his deep sense of humanity. I am very grateful he constantly supported me in my extra-university activities.

I would like to thank Tobias Müller and Claudio Sfreddo for accepting being part of the thesis Committee and for all their very valuable comments. In particular, my gratitude goes to Daniel Kaufmann for his commitment and support as Committee president.

A special thanks goes to Joséphine for her involvment in the productive –and less productive– moments when writing our common chapter and to Luciano, who helped me get this PhD position. Thanks to my closest colleagues for the intensive coffee breaks and support, Caspar, Cécile, Evert, Géraud, Ghislaine, Ivan, Jeremy, Laurent, Martin, Pierluigi, Sandra, Stefano and Sylvain. Special thanks go to Alexandra Kis, David Ardia, Joséphine Leuba, Juliette Cattin and Luciano López. In addition, I thank Nicole Mathys for her priceless advices throughout the thesis.

Finally, I would like to thank my family, Odile, François, Séverin, Nicolas, Chiara, Marie-Jeanne, Oscar, Charline, Agathe, Max, Sacha and, in particular, my precious wife Mireille. She supported me and stood by me in the storm. Thanks to my four-legged friends, Diode, Nash and Fantasio, for the warm welcome when coming back from work. I love you.

General Introduction

1 Motivation and Structure

Spatial constraints are an acute problem within a narrow territory like Switzerland. They guide all economic agents location decisions, and consequently the spatial distribution of population and production. Among the variety of issues that arise from these constraints, I chose to address empirically three of them, which are of particular interest in the Swiss context.

First, where do the most productive Swiss firms locate and in which sectors? Aggregate productivity growth has been notoriously low in Switzerland during the last decades. This average trend probably masks important differences across firms. However, due to the lack of available data at the firm level, and to the best of our knowledge, the precise distribution of productivity performance across Swiss firms is presently unknown.

Second, which type of agglomeration forces attract Swiss firms in a particular cluster? Since the seminal work of Marshall (1920), it has been clearly established that firms tend to co-locate to benefit from agglomeration economies. These forces operate either within a given industry (localization effects) or across industries (urbanization effects). What is the strength of agglomeration economies in Switzerland? And what is their dominant type?

Third, what is the mismatch pattern between income and production across Swiss regions? Households' and firms' location decisions are based on different sets of determinants. As a result, some regions may be highly productive but weakly populated and vice-versa, with important fiscal and mobility consequences. What is the extent of the income-production mismatch in Switzerland?

Is it most acute between or within cantons?

The present thesis provides empirical answers to these issues in four chapters. The first chapter presents the construction of a new set of firm level value-added databases for Switzerland for the period 2011-2015, which are then used in the second chapter to analyze productivity patterns using a methodology derived from the shift-share literature. The observed heterogeneity across firms is further explored in the third chapter by estimating the magnitude and the type of agglomeration economies in Switzerland. Finally, the last chapter sheds light on the spatial mismatch between value-added and income across Swiss municipalities and cantons.

2 Overview

Value-added data in Switzerland are scarce. Lack of coverage and confidentiality issues are two major obstacles for any empirical researcher interested in productivity analyses in Switzerland. The first chapter proposes an innovative solution to both problems. It constructs three value-added datasets, each relying on their own assumptions, for the period 2011-2015 and at a convenient level of disaggregation. To do so, it relies on the official source of value-added data in Switzerland, i.e. the value-added statistics (Wertschöpftungsstatistik, WS). This yearly survey covering around 22'000 firms presents two major challenges. First, each year one fifth of small firms are renewed leading to an unbalanced panel structure (or equivalently, a missing data problem). Second, this survey is conducted at the firm level (administrative unit) rather than at the plant level (productive unit), which is hindering a proper geographical analysis of value creation as a large share of big firms operates multiple plants in different locations. In addition, the Federal Statistical Office (FSO) imposes to aggregate data[1] to preserve confidentiality of the survey respondents. This last constraint has important implications, in particular, the time consistency of the observed units (*pseudo-firms*) is not guaranteed as some firms drop out of the survey because of rollover or non-response. A solution is therefore needed to account for firms dropping out from the sample and to distribute firms value-added on their respective plants. One way to do so is to work with a *restricted* sample by keeping only single plant firms that are present during the entire time pe-

[1] This level of aggregation, called *pseudo-firm*, corresponds to: municipality, industry NOGA 4, legal form.

riod. This drastically reduces the size of the sample. We therefore propose two alternative solutions, which rely on an external source of employment data[2] to enlarge the *restricted* sample. We use either simple *naive* proportionality rules or regression-based rules in a *multiple imputation* framework. The former maximizes the size of the sample but comes with strong assumptions on productivity growth. The latter allows for the introduction of control variables but at the cost of a loss in the number of observations. These two imputations methods help in recovering small units and to enlarge significantly the sample size. Furthermore, we construct two sets of weights to reduce the dominance of large firms in the original sample.

The second chapter makes use of the data constructed in the first chapter. Switzerland is a natural candidate for productivity analyses because of the heterogeneity of economic and social policies across cantons and municipalities. Using a decomposition technique inspired from the shift-share analysis literature, we characterize and decompose productivity growth performance into three structural forces plus a competitive effect across Swiss geographical units (major regions or cantons) over the 2011-2015 period. After having pointed out general trends at the most aggregated level (7 major regions and 13 NACE+ industrial sectors), we "zoom" into the Swiss industrial and geographical landscape. We show that competitive effects dominate at a high level of aggregation, but when we increment the number of geographical units (from major regions to cantons) and/or industrial categories (from NACE+ to NOGA 4 sectors) structural effects appear and do matter. Another striking result is the heterogeneity among each major region: the observed pattern at the regional level does not simply replicate at the level of the respective cantons. Similarly, year-to-year fluctuations do not necessarily reproduce the productivity patterns identified over the whole period (2011-2015). Besides, more variation is found across geographical units than industrial ones.

Why do we observe substantial differences across regions and industries? A potential explanation is the presence of agglomeration economies, which are estimated in the third chapter. Among the many different approaches, only a few allow for a rigorous identification of the agglomeration economies at work. This chapter follows the two-step methodology developed by Jofre-Monseny et al. (2014), which tackles the endogeneity problems discussed in the litera-

[2]The *Statistique des Entreprises* (STATENT) database, which is an exhaustive employment FSO census available at the plant and firm levels.

ture. The first step decomposes agglomeration economies into localization and urbanization effects, the former being productivity gains arising from spatial concentration within a specific industry, the latter referring to productivity gains generated by the spatial concentration of economic activity as a whole (Rosenthal and Strange (2004)). This is done in a Poisson regression framework, using FSO data on employment (STATENT) and newly established firms per industry and municipality (*Démographie des entreprises*, UDEMO). The second step explains the respective identified agglomeration economies on the basis of several determinants suggested by the Marshallian theory of agglomeration, i.e. labour market pooling, input sharing and knowledge spillovers (Marshall (1920)). Evidence of both localization and urbanization economies are found in Switzerland, the latter being larger in magnitude. This result might be linked to the high density of the Swiss urban environment. This third chapter confirms the negative relationship between the two types of agglomeration economies discussed by Jofre-Monseny et al. (2014). The results of the second step indicate a possible answer: industries characterized by a high degree of specificity exhibit strong localization effects and tend to cluster in similar areas, irrespectively of the size of the agglomeration. On the contrary, broad-based industries, which tend to locate in large urban areas, suffer from being in highly specialized regions.

The last chapter addresses the issue of regional economic performance in a broader sense. Focusing only on firms value-added omits the possibility for a municipality to specialize in attracting rich households (rather than productive firms) to ensure its development. In other words, the value created in a given region does not necessarily end up in this region as income. This potential mismatch between income and production can be explained by the theoretical framework of Borck et al. (2009). This spatial general equilibrium model takes into account trade and commuting cost. If the latter are not prohibitive, the model predicts a concentration of firms and a dispersion of households, which means a concentration of value-added and a dispersion of income. Using the value-added data constructed in the first chapter and income data from the Swiss Federal Tax Office, we are able to confirm the prediction of the model. Moreover, using the ratio between value-added and income as an indicator, we identify productive centers surrounded by “residential” belts. This spatial mismatch between production and income is presently at the core of the fiscal equalization and geographical equity debates among Swiss municipalities.

Chapter 1

Multiple Imputation Techniques: An Application to Swiss Value-Added Data *

1 Introduction

A proper analysis of productivity requires disaggregated data, preferably at the level of the establishment. Incomplete coverage and confidentiality issues often drastically reduce accessibility to these data. Building on census and survey data from the Federal Statistical Office (FSO), we present here a novel way to address both problems, leading to value-added databases for Switzerland at a convenient level of aggregation over the 2011-2015 period.[1]

The official data source for value-added which we use is the *Wertschöpftungsstatistik* (WS) of the FSO. It is a yearly survey of around 22'000 firms

*This paper is co-authored by Jean-Marie Grether (University of Neuchâtel, Faculty of Economics and Business).

[1]We thank Nicole Mathys and Tobias Müller for their recommendations, Sam Banatte, Markus Daeppen and Stephen Sonntag from the FSO for their data support, and participants at the Swiss Society for Economics and Statistics and the PdD seminar of the University of Neuchâtel in June 2019 for their comments. The usual disclaimers apply.

which presents incomplete coverage for two reasons. First, some firms drop from the sample either because of non-response or because they are not sampled anymore, as each year 20% of small firms (less than 50 employees) are replaced. Second, the survey is conducted at the firm level, not at the plant level. Thus, all production of multi-plant firms is reported at a single location (headquarters), hindering a proper geographical analysis. We propose a novel method to estimate missing values and redistribute the value-added of multi-plant firms by relying on additional data sources and applying multiple imputation techniques. This leads to a set of enlarged databases for value-added at the plant level.

In addition to missing data issues, we have to respect confidentiality rules. To do so, we have to aggregate these data at the level of the legal form, the municipality and the NOGA-4 industrial sector.[2] This is what we call a "pseudo-firm" in the present paper. It corresponds to the finest disaggregation level at which value-added data is made available in the final databases.

Section 2 presents the imputation techniques which are used to address firms' dropout and multi-plant firms. They are similar in design, relying mostly on hypotheses regarding productivity growth and on employment figures provided by the *Statistique des Entreprises* (STATENT) database, a FSO census available either at the firm or at the plant level. Section 3 presents the final re-aggregation process at the level of the pseudo-firm. Section 4 presents an overview of the constructed datasets and a comparison with National Accounts figures. Section 5 concludes.

2 Sample selection and imputation strategy

After a brief introduction to multiple imputation techniques, we characterize the missing data pattern and then provide a detailed presentation of the imputation procedures followed to complete the value-added data.

[2] As of 2014, there are 2352 municipalities in Switzerland. NOGA 4-digits is a 615 levels industry classification and the FSO divides firms into 23 different legal forms.

2.1 Dealing with missing values through (multiple) imputation

Missing data are a prevalent source of concern for the empirical researcher. Broadly speaking, there are three ways to address this concern, each one of them being considered in the present work (see Schafer and Graham (2002) for a technical discussion). The first obvious way of dealing with missing data is to keep only non-missing cases in a *restricted sample*. Such an option is easily implemented but will bias the results of the analysis if there are structural differences between the observed and the missing data. The second option is to rely on additional data sources (employment in our case) to impute values on the missing variables by using simple rules e.g. proportional or mean-preserving attributions. This type of *naive* imputation methods enlarges the sample size but fails to take properly into account the potential above-mentioned structural differences. The third option also relies on additional data but exploits them more systematically using statistical inference techniques. This third method is the only one that can capture at least part of the structural differences between the missing and the observed data.

A particularly flexible case of the third category is the *multiple imputation* procedure, which repeats the imputation routine m times, leading to a "distribution" for the missing value rather than a point estimate. This allows to take into account the uncertainty around its formation (see Rubin (1987)). Standard procedures can then be applied on the resulting m complete databases. There are several ways of implementing multiple imputation, which mostly depend on the missing data pattern. In our case, as described below, we will follow a simple monotone regression framework.[3]

2.2 Sample selection and enlargement

As mentioned above, our value-added database results from the combination of the WS survey and the STATENT census at the firm level for five years (2011-2015). The WS sample survey covers around 22'000 firms with at least three employees in the secondary and tertiary sectors except bank and insur-

[3] Yuan (1994) provides a detailed presentation. He also identifies three steps in any multiple imputation procedure. First, m estimates are formed for each missing value. Then any required analysis can be applied to each of the m datasets. Finally, the results are combined in a valid statistical way (Rubin (1987)).

ance companies. Large and medium-sized firms (50 employees or above) are all present in the survey. For small firms (between 3 and 49 employees), the sample is stratified according to 2-digit NOGA sectors and size categories based on the number of employees. Small firms are only kept five years in the sample, which means that every year, 20% of them are renewed. The response rate is around 90% for large firms, 70% for medium-sized ones and 55% for small ones.[4]

We first match the two databases at the firm level and compute value-added as the difference between gross output and intermediate consumption. Then we eliminate from the sample all firms which are not present in the WS survey, or never respond, or exhibit a zero or negative value-added at any given year (this to avoid unrealistic estimates in the multiple imputation procedure). This leads to a temporary sample of approximately 14'000 observations per year, among which around 55% (i.e. 7'700) are small firms.

This intermediate sample is still unsatisfactory for analysis because of missing data due to the rollover of small firms or non-responses, and because the value-added of multi-plant firms is concentrated at the headquarters' location. A number of steps are necessary to obtain more suitable databases. These steps are stylized in Figure 1.

A first step is to limit the analysis to those firms that are not replaced, are always responding, and remain single plants (or multi-plant but always active within the same pseudo-firm i.e. the same combination of legal form, municipality and four digit sector). This corresponds to the *restricted sample* represented by the top left cell of the shaded area of Figure 1. This sample is biased towards medium to large firms (unaffected by the rollover problem and responding more than small firms) and excludes multi-plant firms by definition. The number of firms drops to less than 4'000 per year.

Starting from this minimum benchmark, two enlargements are proposed, both of them relying on imputation techniques. The second step allows to enlarging the database using employment (and other) data to infer missing values due to non-response and firms' rollover. This corresponds to the intermediate left cell of Figure 1. At that stage, small firms are better represented, but multi-plant firms are still absent. The third and final step corresponds to

[4] See https://www.bfs.admin.ch/bfs/en/home/statistics/industry-services/surveys/ws.assetdetail.926303.html

Figure 1: Sample selection and enlargement.

<table>
<tr><th colspan="6">Across the 2011-2015 period, is the firm...</th></tr>
<tr><th>...suitable for inclusion?[1]</th><th>...always sampled when it is active?[2]</th><th>...always responding when it is sampled?</th><th>...single plant?[3]</th><th>...multi-plant?</th></tr>
<tr><td>YES</td><td>YES</td><td>YES</td><td>1. Restricted sample</td><td rowspan="3">3. Multi-plant enlargement</td></tr>
<tr><td></td><td>YES</td><td>NO</td><td rowspan="2">2a. Non-response enlargement
2b. Rollover enlargement</td></tr>
<tr><td></td><td>NO</td><td>YES/NO</td></tr>
<tr><td>NO</td><td></td><td></td><td colspan="2">Not considered</td></tr>
</table>

[1] for at least one year, the firm is sampled and responding; it is not reporting negative value-added.
[2] a firm is considered active when it reports positive employment in the STATENT census.
[3] also includes multi-plant firms which always remain active within the same pseudo-firm.

re-distributing value-added across the various units of multi-plant firms, represented by the shaded right cell of Figure 1. The consecutive increase in observations depends on both the type of enlargement and the imputation method, as sequentially discussed below.

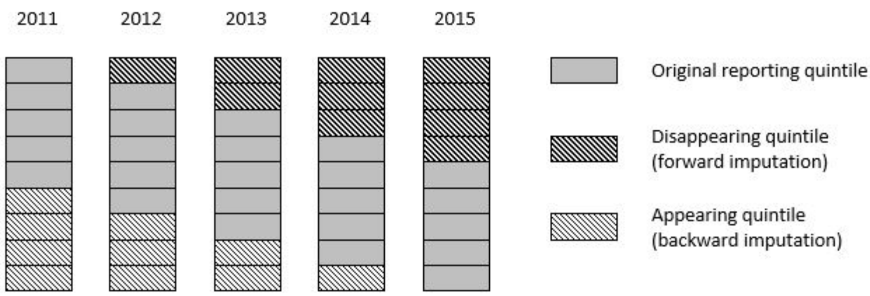
2.3 Enlargement types

Non-response and rollover enlargement

Among eligible firms, and for certain years, some of them do not answer to the WS questionnaire while others disappear from the sample due to the yearly rollover of a quintile of small firms. Imputing value-added to these missing cases enlarges the sample.

Figure 2 illustrates this enlargement effect in the pure rollover case. Each year, one quintile disappears – the "old" quintile – and another one appears – the "new" quintile –. Forward imputation of the old quintiles and backward imputation of the new quintiles increases the number of observations. In the final sample 4/9th (around 45%) of observations have been imputed.

Figure 2: Stylized firm-rollover imputation.



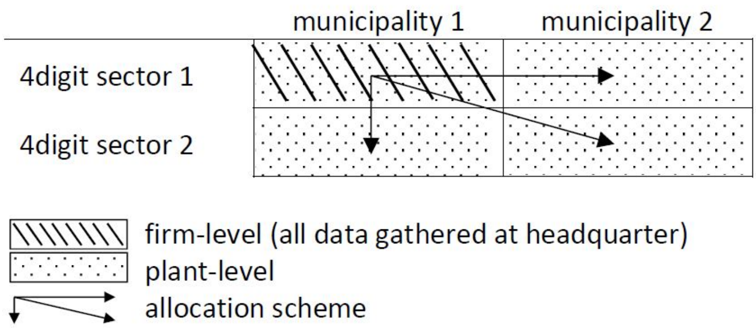
This is a lower bound given that our stylized reasoning so far abstracts from the non-response problem. In reality, accounting for both non-response and rollover, the share of imputed observations turns out to be 54% for small plants (less than 50 employees), 16% for medium firms (between 50 and 499 employees), and 5% for large firms (more than 499 employees).

Multi-plant enlargement

So far, the enlargement process has followed the WS survey definition of the reporting unit, which is the firm, not the plant. For multi-plant firms that are active across several municipalities and/or 4-digit sectors, this is a problem (recall from the introduction that plant level data will have to be re-aggregated anyway at the level of the pseudo-firm for confidentiality reasons). More precisely, when using firm-level data, the presence of multi-plant firms leads to mixing together different 4-digits activities into a single 4-digit one and to mixing together plants in different municipalities into a single one (see Figure 3). These biases are too severe to be acceptable in any study analyzing the interconnections between performance and localization of productive units.

Thus, the second enlargement consists of re-distributing the value-added among the different units of multi-plant firms. To do this, we have to estimate value-added shares or *allocation schemes* through an imputation process which is again mostly based on employment data.

Figure 3: Re-distribution of value-added within multi-plants.



2.4 Imputation methods

To enlarge the sample according to the two above-mentioned procedures, we rely on two imputation methods.

Naive imputation

The first method, or naive imputation, consists of using employment (full time equivalent) shares available from the STATENT census. In the multi-plant enlargement case, the "allocation scheme" is simply the share of each plant in total employment of the multi-plant firm. For the other enlargement cases, we combine STATENT shares with aggregate value added data from the National Accounts. More specifically, for every firm that is affected by rollover or non-response in a given year, we proceed as follows:

(i) A first set of value-added estimates at the firm level is obtained by assuming that value-added remains proportional to full time employment equivalents from the given to the closest year. We keep 2011 figures unchanged but adjust 2012-2015 figures in the rest of the procedure.

(ii) For 2012, we sum up value-added estimates across all imputed firms of a given sector (k). This gives us a first total for value-added of the missing value firms, denoted by TV_k^1.

(iii) From the National Accounts, we obtain the 2011-2012 growth rate of labor productivity at the sector level, denoted by γ_k^n, and we posit it also applies at the level of the completed sample. This, combined with aggregated STATENT and WS data, allows to compute a second figure for the total value-added of the missing value firms, denoted by TV_k^2. [5]

(iv) To make 2012 firm-level data consistent with national account figures, we multiply all value-added estimates obtained at step (i) at the firm level by the TV_k^2/TV_k^1 ratio.

(v) Steps ii-iv are repeated for the remaining three consecutive years, *mutatis mutandis.*

This adjusted proportionality rule ensures that the growth rate of labor productivity in the constructed sample is consistent with the reported growth rate from the National Accounts.

Multiple imputation

The second method consists of applying a multiple imputation procedure based on Rubin (1987). For the implementation, we use the multiple imputation

[5] The demonstration is as follows. Let us denote value added by V, labor (full time equivalent) by L, the sector by k, the national level by n, the sample level by s, and any growth rate by a hat i.e ($\hat{}$). Assuming identical labor productivity growth rates at the sample and national level leads to $[(1+\hat{V}_k^n)/(1+\hat{L}_k^n)]-1=[(1+\hat{V}_k^s)/(1+\hat{L}_k^s)]-1$. In the previous expression, the sample value added growth rate ($\hat{V}_k^s$) can be replaced by a weighted average of the missing firms value added growth rate ($V_{k,mv}^s$) and the incumbent firms value added growth rate ($V_{k,ic}^s$), i.e. $\hat{V}_k^s=\theta_k^s\cdot\hat{V}_{k,ic}^s+(1-\theta_k^s)\cdot\hat{V}_{k,mv}^s$, where $\theta_k^s=V_{k,ic}^s/V_k^s$. After simplification we obtain:

$$\hat{V}_{k,mv}^s=\frac{(1+\gamma_k^n)(1+\hat{L}_k^s)-(1+\theta_k^s\hat{V}_{k,ic}^s)}{1-\theta_k^s}$$

Applying the above growth rate (bounded between -50% and +50% as a feasibility constraint) to the firms with missing values and summing up leads to the second estimated total for the sectoral value added, TV_k^2.

PROC MI routine proposed by SAS (SAS Institute Inc. (2015)), using a monotone regression framework.[6] Whatever the enlargement type, we estimate the value added of the corresponding unit (the firm for the non-response and rollover cases, the plant for the multi-plant case) performing the following steps:

(i) Regression of the natural logarithm of value added (V) on the natural logarithm of employment (full time equivalent, L) and a set of categorical variables that includes year, 3-digits sector, district and legal form.

$$ln(V) = \beta_0 + \beta_1 \cdot ln(L) + \alpha_j + \gamma_i + y_t + \omega_f$$

Where α_i, γ_i, y_t and ω_f are fixed effects capturing, respectively, the sectoral effect of belonging to 3-digits industry j, district i, year t and legal form f.[7]

We control for stand-alone cases where there is no reported observation because there has been a change of the sector, region, or legal form during the sample period. We also control for dummy outliers. To do so, we run a trial imputation (only two runs) without variables log-transformation and we define as outliers those specific industries, districts or legal forms with an estimated coefficient that deviates by more than two standard deviations from their classes' means. All firms that correspond to the identified stand-alone or outlier cases are dropped from subsequent analysis.

(ii) New parameters $\tilde{\beta} = (\tilde{\beta}_0, \tilde{\beta}_1, \tilde{\alpha}_j, \tilde{\gamma}_i, \tilde{y}_t, \tilde{\omega}_f)$ and variance $\tilde{\sigma}^2$ are simulated from the estimated parameters of the above regression, $(\hat{\beta}_0, \hat{\beta}_1, \hat{\alpha}_j, \hat{\gamma}_i, \hat{y}_t, \hat{\omega}_f)$, and estimated variance $\hat{\sigma}^2$.

$$\tilde{\sigma}^2 = \hat{\sigma}^2 \ \frac{n-k-1}{g}$$

[6] Note that unfortunately, the alternative SAS procedure that imputes the closest observed values (predictive mean matching) is too time-consuming to be implementable in our case.

[7] The original specification was run for each monetary variable separately (i.e. gross output and intermediate consumption) and included more than 2800 dummies, in particular all municipalities and 4-digit sectors. Many dummies turned out non significant but were nevertheless used in the imputation procedure. As many municipalities had too few observations, this led to unrealistically low or high figures for imputed value-added. Therefore, a unique specification for value-added was selected, with substantially less dummies (slightly more than 400) by replacing municipalities with districts and 4-digit by 3-digit sectors.

where n is the number of non-missing observations, k the number of explanatory variables and $g \sim \chi^2_{n-k-1}$.

$$\tilde{\beta} = \hat{\beta} + \tilde{\sigma} W_h' Z$$

where $W = W_h' W_h$ and W_h is obtained by the Cholesky decomposition of W. Z is a vector of $k+1$ normalized random variables.

(iii) Then predicted values ($\tilde{V}$) are formed using these new coefficients. For each missing observation, belonging to industry j, located in municipality i and year t:

$$\tilde{V} = exp[\tilde{\beta}_0 + \tilde{\beta}_1 \cdot ln(L) + \tilde{\alpha}_j + \tilde{\gamma}_i + \tilde{y}_t + \tilde{\omega}_f + z\tilde{\sigma}]$$

where z is a normal standard deviation.

(iv) The procedure is repeated m times with m being the number of imputations. The efficiency of the estimators depends on the number of imputations. For a relative high fraction of missing information, Graham et al. (2007) recommend a high number of imputations, up to 40 if half of the observations are missing . To balance estimator efficiency and computing time, we have selected 20 imputations, a reasonable number according to Graham et al. (2007) when 30% of observations are missing.

2.5 Combining imputation procedures

We proceed by implementing the various imputations techniques for the non-response and rollover enlargements. This leads to $m + 2$ firm-level databases (including the restricted sample and the one obtained by the naive imputation method), corresponding to the first column of Figure 4. These databases are then converted into $(n + 1)(m + 2)$ plant-level databases by the multi-plant enlargement (remaining columns of Figure 4), applying the allocation schemes obtained through the naive or multiple imputation techniques.[8]

[8] See Figure A.1 in the Appendix for a schematic representation of the sequence of imputations for the m=n=2 case.

Figure 4: Stylized imputation strategy.

			Multi-plant enlargement					
			No imputation	Naive imputation	Multiple imputation (j)			
			0	I	1	2	...	n
	No imputation	0	$A_{0,0}$ (3'600)	(5'600)	(5'000)	(5'000)	(5'000)	(5'000)
Non-response & Rollover enlargement	Naive imputation	I	(20'000)	$A_{I,I}$ (24'000)	(22'000)	(22'000)	(22'000)	(22'000)
	Multiple imputation (i)	1	(17'500)	(21'000)	$A_{i\geq1,j\geq1}$ (18'000)			
		2	(17'500)	(21'000)				
		...	(17'500)	(21'000)				
		m	(17'500)	(21'000)				

Notes: Number of firms per year between parentheses. No imputation means keeping only the restricted sample (see Figure 1); Naive imputation is based on employment share only; Multiple imputation is based on a multivariate regression and is repeated m(n) times. Dashed zones correspond to alternative datasets for robustness. A_{00}: dataset including only firms of the restricted sample (no imputation). A_{II}: dataset including all firms from the WS survey. $A_{i\geq1,j\geq1}$: datasets including all firms from the WS survey minus outliers and stand-alone cases.

The rounded average number of firms per year is indicated between parentheses in Figure 4. As expected, the restricted sample, which is limited to single-plant or non-problematic multi-plant firms reporting positive value-added every year they are active, is small (3'600 firms per year) and biased towards large firms. Combining naive imputation techniques for firms' non-response, rollover and multi-plant firms maximizes the number of firms in the sample (24'000 per year). Using multiple imputation techniques instead still increases the number of firms vis-à-vis the restricted sample but to a lower extent (18'000 firms per year), due to the elimination of outliers and stand-alone cases.

3 Aggregation to *pseudo-firms*

In a final step, to maintain confidentiality, we re-aggregate all the plant-level databases obtained from the previous stages at the level of unique combinations of 4-digit sector, municipality and legal form. Each combination is called a "pseudo-firm".

To document this final aggregation step we calculate (in addition to the value-added and employment data) the following indicators for each pseudo-firm: number of plants, number of firms, number of active 6-digits sectors and coefficient of variation of full time employment across plants. We also construct two employment-related variables which are necessary to locate and weight the pseudo-firms in the final sample:

1. The employment-weighted geographic coordinates of the economic center of gravity of the pseudo-firms, which allow their spatial localizations (see Figure B.1 in the Appendix for an example).

2. The weight attributed to each pseudo-firm, which is obtained according to one of the three procedures described described below.

Whatever the procedure followed to construct pseudo-firm weights, it has to respect two principles. In the initial WS sample, weights are attributed so that, if all firms were to respond, the sum of weight-inflated employment figures would be equal to total true employment in the whole (STATENT) population. The first principle is to adjust weights in order to maintain this desirable property in each (pseudo-firm level) final sample. As a result, whatever the sample, the employment-weighted total is always the same, and the difference with respect to total employment is due to non-response. Another source of concern is that some firms disappear and other re-introduced through the selection and imputation processes described above. It is therefore not guaranteed that the distribution of pseudo-firms in the final sample is representative of the observed distribution of firms in the whole population. The second principle is to adjust weights in order to minimize the difference between the probability density function of pseudo-firms in the final sample and the converse density function obtained from the STATENT population.

3.1 Aggregation of original sampling weights

A first way to comply with the above-mentioned principles, is simply to aggregate reported weights in the original WS sample. We proceed as follows:

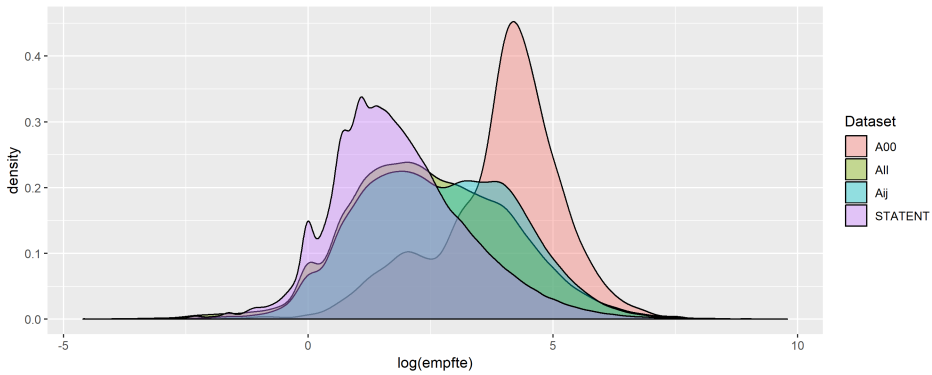
1. We calculate the sum of weight-inflated employment figures (full time equivalents) in the initial WS sample, denoted by L_I.
2. If, for a given year, the firm is present in the final sample but missing in the original sample, we impute for that year the average observed weight when the firm is not missing. Then we calculate the sum of weight-inflated employment figures (full time equivalents) in the final sample, denoted by L_F.
3. We calculate firm-level adjusted weights as the product between the original weight and the L_I/L_F ratio.
4. We assume identical adjusted weights across all plants of a given multi-plant firm.
5. When aggregating from the plant to the pseudo-firm level, we calculate the adjusted-weight of the pseudo-firm as the employment-weighted average of the adjusted weights of all plants belonging to that same pseudo-firm.

This first set of weights improves the matching between the distribution of employment in the final samples and the distribution of employment in the whole population. This is illustrated in Figures 5 and 6 comparing kernels of employment (full-time equivalent) probability density functions (pdf), for year 2015, for each type of final database defined in Figure 4 ($A_{0,0}$, $A_{I,I}$ and $A_{i,j}$, see Figure 4) and also for the whole reference population i.e. the database obtained when aggregating STATENT data at the level of pseudo-firms.[9]

Regarding non-weighted data (Figure 5), as could be expected, the contrast is striking between the population (STATENT purple curve) and the restricted sample ($A_{0,0}$ pink curve), which is biased towards large firms. The two imputed samples (either $A_{I,I}$ or $A_{i,j}$, green and blue curves) lie as intermediate cases between these two extremes. As it should be, applying weights to the restricted and imputed samples drastically reduces these differences, as illustrated by Figure 6, where all four pdfs now overlap more closely. Results for all years are similar, they are reported in Figures C.1, C.2 and C.3 in the Appendix.

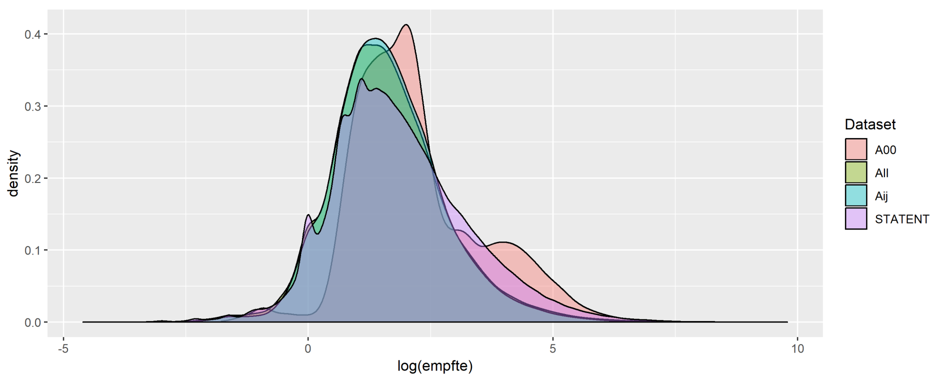
[9] As the WS survey is not supposed to include firms with less than three employees, those are dropped from STATENT data, except if the report more than two employees during at least one year. Sectors A, K and U are not officially covered by the WS, so there are also dropped from all databases.

Figure 5: Non-weighted density functions for full-time employment equivalents, 2015.



Notes: See Figure 4 for a description of datasets A_{00}, A_{II} and A_{ij}

Figure 6: Weighted density functions for full-time employment equivalents, 2015



Notes: See Figure 4 for a description of datasets A_{00}, A_{II} and A_{ij}

At closer look however, there remains differences in shape, and although these differences are stronger for $A_{0,0}$ (which is due to the fact that this database is biased towards large firms) they are also present for $A_{I,I}$ and $A_{i,j}$. More precisely, with respect to the reference population, the pdf of the imputed samples are larger for small and medium range pseudo-firms, and smaller for large pseudo-firms. In other words, it suggests that these preliminary weights are too large at the bottom of the distribution. This is due to the enlargement of the database towards small firms, and requires further adjustments of the weights, as performed by the two following procedures.

3.2 Adjusted weights I: Proportional downsizing

The first procedure to adjust weights consists of finding the most appropriate mix between no weighting at all (which understates the frequency of small firms) and full weighting (which overstates it). More specifically, for each type of imputed dataset, we calculate an adjusted weight for pseudo-firm p year t given by:

$$\tilde{\omega}_{p,t} = \lambda_t \omega_{p,t} + (1 - \lambda_t)\frac{1}{n_t}$$

where $\omega_{p,t}$ is the original (normalised[10]) weight, $\tilde{\omega}_{p,t}$ the adjusted weight, n_t the number of pseudo-firms and λ_t the optimisation parameter, $\lambda_t \in [0, 1]$. These adjusted weights are then re-scaled so that the sum of weighted employment figures remains unchanged, as for the weights of subsection 3.1.

We determine numerically the optimal value of λ by 0.01 increments. Figure 7 reports the results for 2015. It turns out that the area is minimised at $\lambda = 1$ for $A_{0,0}$, $\lambda = 0.69$ for $A_{I,I}$ and $\lambda = 0.73$ for $A_{i,j}$. Figure 8 illustrates the impact of the optimisation process on the overlap between the two pdf for the multiple imputation sample ($A_{i,j}$). Results for the other samples and years are very similar and available upon request.

[10]To ease calculation of area differences between the density functions by the R package, weights are normalised so that their sum is equal to 1.

Figure 7: Optimal values of the weighted average parameter (λ), 2015.

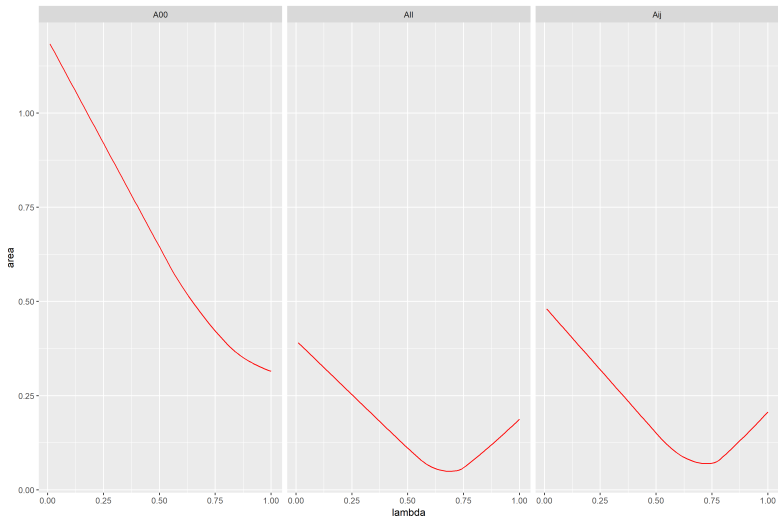
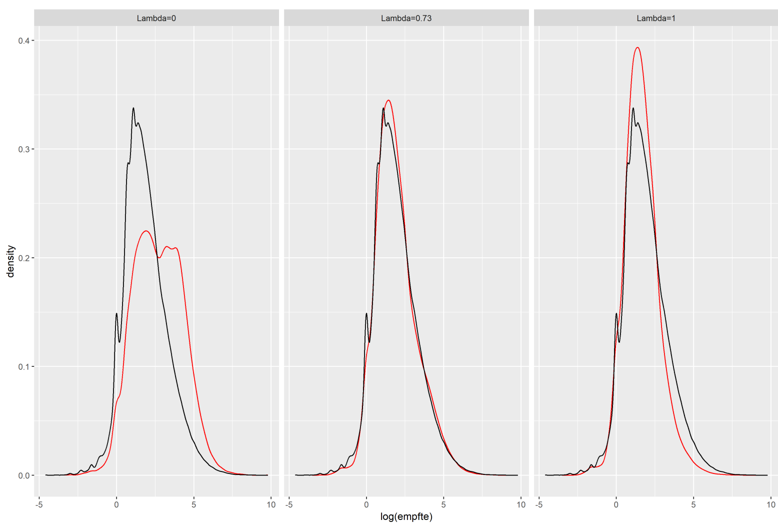


Figure 8: Impact of optimal weights on the matching between the multiple imputation sample and the population, 2015.



3.3 Adjusted weights II: Bottom up reconstruction

Adjustment method I (proportional downsizing) is intuitive but lacks theoretical justification and does not exploit fully the available information. The alternative proposed here is to reconstruct weights from the bottom up, making use of our knowledge of the employment distribution in the sample and over the whole STATENT population.

General procedure

The basic idea is to decompose the population into different strata according to geography (Switzerland, large regions, cantons, districts), industry (NOGA2, NOGA3, NOGA4), legal form (yes, no) and size classes (5, 10 , 15 or 20 size classes, see Figure 9 for a definition). This leads to 96 possible strata definitions (4x3x2x4). For a given definition, the weight of each particular combination is defined as the inverse of the sample full-time employment (FTE) share in total population. Following FSO guidelines, the reference population is the corresponding STATENT excluding sectors A and K and firms with strictly less than three employees during the entire time period. Finally, the best definition of strata is selected by minimizing again the differential area between the population and the sample employment distributions.

Dealing with the "zero-weight" issue

Although straightforward, this procedure cannot be applied directly at the pseudo-firm level. To understand why, imagine that for a given combination of canton, 4digit industry and legal form there are three plants in the STATENT population, with FTE Figures of 4, 8 and 9 respectively. Assume further that we work with 15 size classes (third line of Figure 9) and that the plant with 4 FTE is not present in the sample (a frequent case as small firms are under-represented in the WS sample). This leads to a sample pseudo-firm employment of 17, versus 23 for the whole population. As the threshold is 20 between size classes 8 and 9 (see Figure 9), this leads to a weight of zero for class 8 and no reported employment for class 9, i.e. a complete loss of all the available information. Working at the firm rather than the pseudo-firm level does not necessarily solve this *zero-weight* problem (for example if the smallest and largest plant of the previous example belong to the same firm misclassification also happens).

Figure 9: Full-time employment (FTE): Size classes definitions.

<table>
<tr><td>5 size classes</td><td colspan="5">0</td><td colspan="8">1</td><td></td></tr>
<tr><td>10 size classes</td><td>0</td><td>1</td><td>2</td><td colspan="2">3</td><td colspan="2">4</td><td colspan="3">5</td><td colspan="3">6</td><td></td></tr>
<tr><td>15 size classes</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td colspan="2">7</td><td>8</td><td colspan="2">9</td><td>10</td><td></td></tr>
<tr><td>20 size classes</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td></td></tr>
<tr><td>FTE</td><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>7.5</td><td>10</td><td>12.5</td><td>15</td><td>20</td><td>25</td><td>30</td><td>40</td></tr>
</table>

<table>
<tr><td>5 size classes</td><td colspan="4">2</td><td colspan="2">3</td><td>4</td></tr>
<tr><td>10 size classes</td><td colspan="4">7</td><td colspan="2">8</td><td>9</td></tr>
<tr><td>15 size classes</td><td colspan="2">11</td><td colspan="2">12</td><td colspan="2">13</td><td>14</td></tr>
<tr><td>20 size classes</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td><td>18</td><td>19</td></tr>
<tr><td>FTE</td><td>40</td><td>50</td><td>60</td><td>80</td><td>100</td><td>150</td><td>250</td></tr>
</table>

Notes : Class size numbers in italic / upper bound not included in the interval.

At the end of the day, the only way to eradicate the zero-weight problem is to define weights at the plant level. However, at this stage of the procedure, we have no access to plant-level data anymore as we are already dealing with pseudo-firm (i.e. aggregated) data. Thus, we need to recover plant-level data exploiting the available information we have in STATENT and in the variables created during the pseudo-firm aggregation. We proceed in three steps (see Appendix A.6 for a more detailed description of step 3):

1. **Direct calculation**. When the pseudo-firm has less than 3 plants, knowledge of the mean ($\bar{X}$) and the variation coefficient (VC) is sufficient to calculate plant level FTE ($\bar{X}$ if there is a single plant, $\bar{X} \pm \frac{VC}{\sqrt{2}}$ if there are two plants). This corresponds to 94.5% of pseudo-firms (71% of total FTE).

2. **Combinatory analysis**. For pseudo-firms with a number of plants which is larger than two but sufficiently close to the total number of plants in STATENT, the exact combination of plants within the pseudo-firm can be retrieved computationally in a reasonable time. Let us denote by n the number of plants of the pseudo-firm, and N the number of plants for the same combination of municipality, NOGA4 and legal form values in

STATENT. Then, among all the possible C_n^N combinations of n out of N plants, and provided $C_n^N < 75000$ (threshold determined by trial and error) one identifies the unique combination that leads to the same $\bar{X}$ as the one reported for the pseudo-firm (calculating the VC constitutes a proof). This corresponds to 4.5% of pseudo-firms (17% of total FTE).

3. **Gamma distribution**. For all remaining cases (1% of pseudo-firms, 12% of total FTE, i.e. essentially large pseudo-firms with many plants), we assume that plants' employment follows a Gamma distribution and distribute total FTE across plants in accordance with the reported values for n, VC and $\bar{X}$. This generates some zero-weight cases. We eliminate these cases by reshuffling employment across plants in non-zero weight categories, working with the maximum number of size classes (20) and along a systematic procedure described in Appendix A.6.

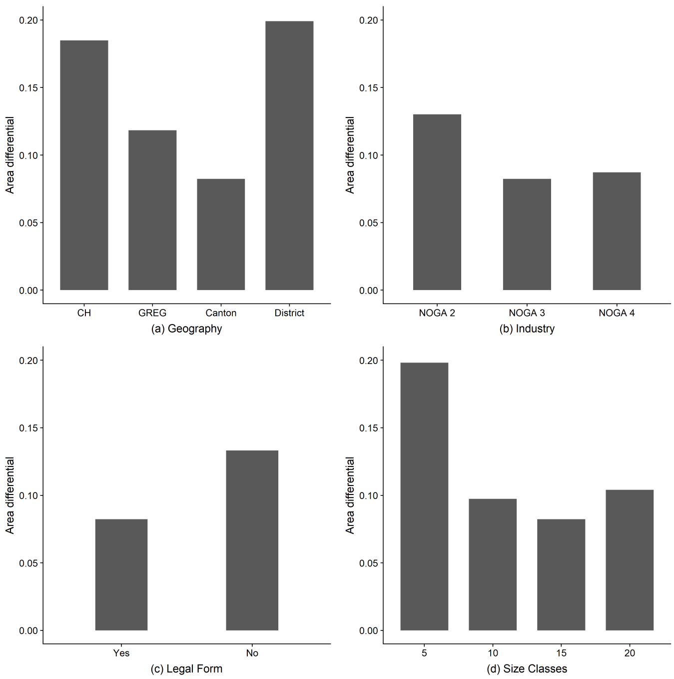
Steps 2 and 3 above are rather time consuming so their application is limited to the multiple imputation case ($A_{i,j}$ in Figure 4). Moreover, they imply small adjustments of the reference population.[11]

Selecting the optimal strata definition

Once plant-level employment figures have been recovered, plant-level weight are calculated (inverse of employment share) and re-aggregated back as employment weighted averages at the pseudo-firm level. Some categories combinations are present in the population but not in our sample. To recover this missing employment, we inflate all weights by a common factor. These calculations are performed for each one of the 96 above-mentioned strata definitions. We select the most appropriate definition following the same criterion as in the previous section i.e. by minimizing the difference, in terms of area, between the population and sample employment densities. Figure 10 shows that the best strata definition turns out to be canton, NOGA3, including legal form and 15 size classes.

[11] When it is not possible to find a combination in step 2 that perfectly matches the reported $\bar{X}$ for the pseudo-firm, the selected sample is enriched by all available observations from the complete STATENT database (i.e. including plants with less than three employees during the entire time period) for that particular set of year, municipality, NOGA4 and legal form values. This affects 98 pseudo-firms (i.e. 0.11% of the total). A similar enlargement of the reference population is necessary for 62 pseudo-firms in step 3 (i.e. 0.07% of the total).

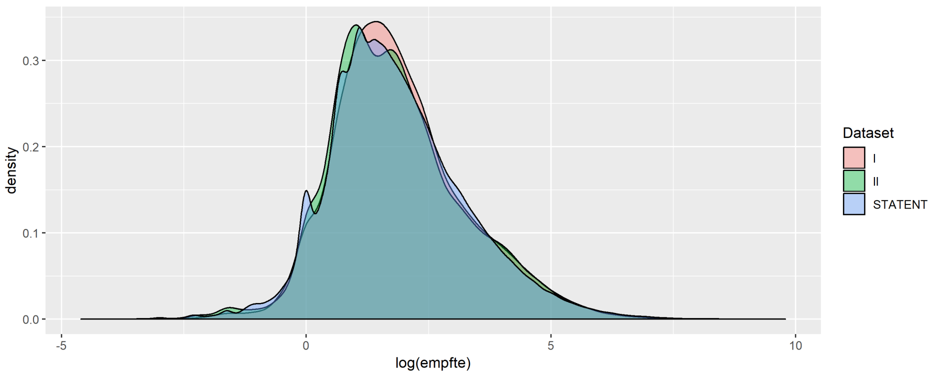
Figure 10: Selection of the most appropriate strata definition.



Notes : average differential area between the $A_{i,j}$ sample and the population density / in each panel the values of the other dimensions are set at their optimal level i.e. canton, NOGA3, legal form and 15 size classes.

As illustrated by Figure 11, the bottom-up adjustment method (weights II, in green) provides a better fit of the population distribution (in blue) than the proportional downsizing methods (weights I, in pink). On average over the 2011-2015 period, the differential area between the sample and the population employment densities is 0.091 for weights I (proportional downsizing method) and 0.082 for weights II (bottom-up method).

Figure 11: Comparison of the two adjusted weights methods, $A_{i,j}$ (2015).



4 Data Overview

4.1 Data summary

Table 1 summarizes the characteristics of the main databases generated by the imputation procedures. Beware that observations here correspond to pseudo-firms, while in Figure 4 the numbers between parenthesis correspond to firms. Whatever the sample, the number of pseudo-firms is almost constant over time, as entry/exit rates are roughly similar. The restricted sample, $A_{0,0}$, is the smallest database, with less than 3000 yearly observations. The number of plants is not much larger. This is normal, as the restricted sample is mostly composed of relatively large single-plant firms, with only some non-problematic multi-plant firms with all plants in the same pseudo-firm. The naive imputations ($A_{I,I}$) considerably increase the sample size, in terms of pseudo firms, due to the non-response and rollover enlargements, and even more in terms of plants, due to the multi-plant enlargement. On average, the multiple imputations sample ($A_{i,j}$) is around twice smaller than the naive imputation sample, due to the elimination of outliers and stand-alone cases. However, it remains considerably larger than the restricted sample (6 times larger in terms of pseudo-firms, 8 times in terms of plants).

Regarding the composition of each database, it appears that the restricted sample pseudo-firm is on average twice larger than in the other two databases (around 100 full time-equivalent vs. 50). It is also more productive (around CHF

Table 1: Summary statistics of the datasets.

Dataset	Year	Number*	N new△	Number of plants	Full-time equivalent Min	Max	Mean	CV	Value added** Min	Max	Mean	CV	Share of municipalities covered	Total employment share† non-weighted	Total value-added share†† non-weighted	weighted (I)	weighted (II)
$A_{0,0}$	2011	2936		3174	0.2	8170.98	93.8	2.12	6.0	3540885.80	22463.4	5.53	39.5%	8.37%	12.43%	121.11%	/
	2012	2812	67	3052	0.3	8085.11	97.4	2.07	8.0	3920905.00	24582.7	5.96	38.6%	8.26%	12.89%	128.27%	/
	2013	2750	62	2994	0.5	8537.80	100.3	2.12	33.0	3556642.00	24735.3	5.71	38.0%	8.16%	12.47%	127.33%	/
	2014	2753	107	2994	0.2	8549.70	101.8	2.12	12.6	3477452.00	25696.0	5.85	38.3%	8.20%	12.65%	127.24%	/
	2015	2803	147	3059	0.2	8524.84	99.8	2.14	7.7	4183055.00	24838.4	6.06	38.9%	8.15%	12.34%	123.17%	/
$A_{I,I}$	2011	33008		52687	0.0	15868.97	47.1	3.72	0.3	7996248.68	8419.5	8.14	81.2%	47.22%	52.37%	102.64%	/
	2012	33599	1743	53898	0.0	16484.06	46.8	3.81	0.3	8472771.52	8493.6	8.69	81.7%	47.42%	53.22%	104.11%	/
	2013	35006	2861	57630	0.0	16824.98	46.4	3.88	0.7	8354989.67	8410.8	8.44	83.0%	48.03%	53.98%	104.45%	/
	2014	34918	1675	57547	0.0	17268.41	46.9	3.86	1.1	7938707.26	8636.6	8.27	83.1%	47.90%	53.93%	104.49%	/
	2015	34394	1530	56645	0.0	17708.27	47.3	3.87	0.7	8495329.78	8710.2	8.54	82.8%	47.40%	53.09%	104.11%	/
$A_{i,j}$ ▽	2011	17625	/	23878	0.0	15797.35	48.7	3.67	1.0	7896097.33	8535.0	9.22	65.3%	26.07%	28.35%	100.03%	96.96%
									(0.54)	(608705.3)	(18.6)	(0.33)			(0.06)	(0.27)	(0.37)
	2012	17924	834	24365	0.0	16416.76	48.5	3.78	0.9	8403539.36	8311.0	9.82	65.9%	26.20%	27.78%	97.43%	94.49%
									(0.49)	(592480.1)	(21.3)	(0.33)			(0.07)	(0.25)	(0.35)
	2013	17925	794	24398	0.0	16824.98	49.0	3.83	1.0	8259435.51	8392.5	9.61	65.6%	26.00%	27.58%	97.21%	93.93%
									(0.46)	(696976.5)	(23.0)	(0.38)			(0.08)	(0.35)	(0.40)
	2014	17860	794	24342	0.0	17268.41	49.5	3.84	1.1	7741245.10	8608.2	9.11	65.9%	25.88%	27.49%	96.97%	94.43%
									(0.29)	(675973.8)	(15.5)	(0.34)			(0.05)	(0.22)	(0.32)
	2015	17586	808	23934	0.0	17708.27	49.8	3.90	0.5	8362957.38	8736.0	9.55	65.6%	25.53%	27.23%	97.09%	93.50%
									(0.16)	(682613.6)	(18.4)	(0.36)			(0.06)	(0.27)	(0.29)

Notes:
* Number of *pseudo-firms* (unique noga4-municipality-legal form combinations).
△ Number of emerging *pseudo-firms* (i.e. present in the current year but not previous one).
** In thousands CHF.
▽ With $(i, j) \in \{1; 20\}$. In parenthesis, the standard deviation of the given statistics
(i.e. statistics are computed on each of the 400 datasets and the mean and standard deviation of the mean of each statistics are reported (implicitly in hundreds when needed)).
† We exclude sectors A, K, T and U from the reference population, as those sectors are not part of the WS survey. Weighted employment results are not reported as they are identical for all samples due to calibration.
†† We exclude sectors A, K, T and U from the reference population, as those sectors are not part of the WS survey. Weights I and II are defined in, respectively, sections 3.2 and 3.3.

230000 vs. 170000 per full time-equivalent per year). This should not come as a surprise as the imputed samples were basically designed to recover small firms which are rolled over and to split value-added across the various units of multi-plant firms. Both manipulations reduce the average size of the production units. This result is consistent with the structural differences between the various sample types discussed in Section 3.

4.2 Global coverage of employment and value added

The last three columns of Table 1 provide the share of employment and value added covered by the different samples. Consider employment first, the reference population being the STATENT database. As weights are always calibrated in order to match the reference population, there is no point to report the weighted share for employment. Regarding the non-weighted shares, the imputation procedures do increase the coverage of the sample, which is rather low for the restricted sample ($A_{0,0}$), less than 10%, up to more than 25% for the multiple imputation sample ($A_{i,j}$) and slightly less than 50% for the naive imputation sample ($A_{I,I}$).

Regarding value-added, we use as a comparison basis the figures estimated by the National Accounts department of the FSO. They constitute the official reference in Switzerland, and the FSO has taken care over recent years to refine its procedure in order to provide robust estimates of value added at the aggregated level (see (Federal Statistical Office, 2016)). The methodology followed by the FSO also relies partly on the WS database, but it is distinct from the procedure applied in the present paper on several counts (apart from the basic difference in objectives, i.e. we seek to provide firm-level rather than aggregated level estimates). We focus here on the major distinctions. First, it performs only a multiplant enlargement, which means that the non-response and turnover enlargement is not considered. Second, it works at a more aggregated level than we do for sectors (21 instead of 272), plant size categories (10 instead of 15), geographical units (7 instead of 26) and legal forms (none vs. 22). Third, it calibrates its results at the aggregate level in order to make them consistent with other national account calculation approaches for GDP.

Given the above-mentioned differences, imperfect coverage may be expected for our three samples. The total non-weighted value added share is indeed rather low, although slightly larger than for employment. However, and quite surprisingly, there is a rather good match for the weighted figures, particularly for the two imputed samples. The value-added share is around 125% for the restricted sample, again a reflection of the bias of that sample towards large and more productive single plant firms. The imputed samples are more representative of the distribution of firms in the population, and although their weights were obtained from a completely different perspective from the FSO methodology, they achieve a share in total value added which is quite close to 100% (104% for $A_{I,I}$, 95-98% for $A_{i,j}$).

4.3 Detailed coverage of the imputed samples ($A_{I,I}$, $A_{i,j}$)

Pursuing the analysis at a more disaggregated level, Tables 2 and 3 report the coverage rates for large geographic regions and sectors for the two imputed samples (see Figure D.2 in Appendix for the restricted sample). As the naive imputation sample covers a larger share of total employment (around 50% vs. 25% for the multiple imputation sample), it leads naturally to a better employment coverage for large regions, with an approximate range of 90-110% (vs. 50-120% for $A_{i,j}$). This remains valid for value added, and to a lesser extent also for large industry groups, even if the DEPQ share (public utilities, education and health) falls to 40% for employment and 55% for value added. As employment and value added shares are positively correlated, the contrast between the two samples is less stark regarding the productivity ratio. The better coverage of the naive imputation sample must be put in balance with its major drawback namely that its two enlargement procedures are based on the explicit assumption of a constant productivity whether within firms or across periods. This makes it less appropriate than the multiple imputation sample to analyse productivity change at the micro level.

Table 3 also provides the opportunity to compare the two alternative sets of weights for the multiple imputation sample. The global coverage for value added is 3% higher for weight I. However, weights II lead to a smaller coverage range than weights I. This is valid in general, both for employment or value added, and for large regions or large sectors. Moreover, across the 400 databases, the standard deviation is generally smaller for weights II than for weights I. Thus, on balance, it appears that weights II offer a more stable representation of value added and productivity differences across Swiss firms.

Table 2: A_{II} coverage.

	Weigthed* full-time equivalent share	Weighted* value added share†	Productivity share▽
Major regions			
Espace Mittlelland	99.1%	95.0%	95.9%
Région lémanique	95.5%	120.6%	126.3%
Zürich	101.1%	102.4%	101.3%
Nordwestschweiz	108.9%	110.0%	101.1%
Ostschweiz	99.6%	90.8%	91.2%
Zentralschweiz	100.9%	116.1%	115.1%
Ticino	90.7%	78.4%	86.5%
Industries††			
GHIJ	124.5%	144.0%	115.7%
BCF	129.8%	135.4%	104.4%
DEPQ	41.4%	56.6%	136.6%
LMNRS	104.8%	93.3%	89.0%
Total	100.0%	104.0%	104.0%

Notes:
† Share in value added of the national accounts, excluding industries NOGA 1 A,K T and U, which are not covered by WS.
▽Ratio between average productivity in the sample and "national" productivity.
"National" productivity is based on own calculations using national accounts total value added data and STATENT.
* Weights defined in section 3.2.
†† We exclude from the table sector O, which is not present in our sample.

Table 3: A_{ij} coverage.

	Weigthed full-time equivalent share		Weighted value added share†		Productivity ratio▽	
	weights I*	weights II**	weights I	weights II	weights I	weights II
Major regions						
Espace Mittelland	101.3%	99.4%	88.0% (0.36)	82.8% (0.28)	88.5% (0.36)	83.3% (0.29)
Région lémanique	89.7%	97.2%	113.0% (0.50)	116.4% (0.32)	116.2% (0.52)	119.7% (0.33)
Zürich	101.7%	118.7%	104.2% (0.53)	114.0% (0.46)	87.8% (0.44)	96.0% (0.39)
Nordwestschweiz	123.8%	111.1%	130.2% (0.42)	113.5% (0.39)	117.2% (0.38)	102.2% (0.35)
Ostschweiz	114.1%	99.7%	88.6% (0.37)	76.7% (0.43)	88.9% (0.37)	76.9% (0.43)
Zentralschweiz	86.7%	71.2%	68.8% (0.36)	57.6% (0.39)	96.6% (0.50)	80.8% (0.55)
Ticino	44.4%	63.2%	36.6% (0.68)	50.1% (0.38)	58.0% (1.07)	79.2% (0.60)
Industries††						
GHIJ	107.0%	120.2%	126.0% (0.44)	131.4% (0.33)	104.9% (0.36)	109.3% (0.28)
BCF	161.7%	144.5%	160.1% (0.32)	141.4% (0.36)	110.8% (0.22)	97.9% (0.25)
DEPQ	38.4%	35.0%	37.4% (0.21)	33.7% (0.14)	107.1% (0.60)	96.3% (0.40)
LMNRS	88.9%	96.9%	65.6% (0.37)	70.4% (0.30)	67.7% (0.38)	72.6% (0.31)
Total	100.0%	100.0%	97.7% (0.17)	94.7% (0.17)	97.7% (0.17)	94.7% (0.17)

Notes:

† Share in value added of the national accounts, excluding industries NOGA 1 A,K T and U, which are not covered by WS. Standard deviation in parenthesis.

▽ Ratio between average productivity in the sample and "national" productivity. "National" productivity is based on own calculations using national accounts total value added data and STATENT.

* Weights defined in section 3.2.

** Weights defined in section 3.3.

†† We exclude from the table sector O, which is not present in our sample.

5 Conclusion

Data on value-added at the level of the production unit is limited in Switzerland. It is only reported at the firm level, not the plant level, only available for a subsample of relatively large firms, and only reported with other monetary variables, not employment figures. This makes it particularly unsuitable to undertake a proper analysis of productivity at the microeconomic level.

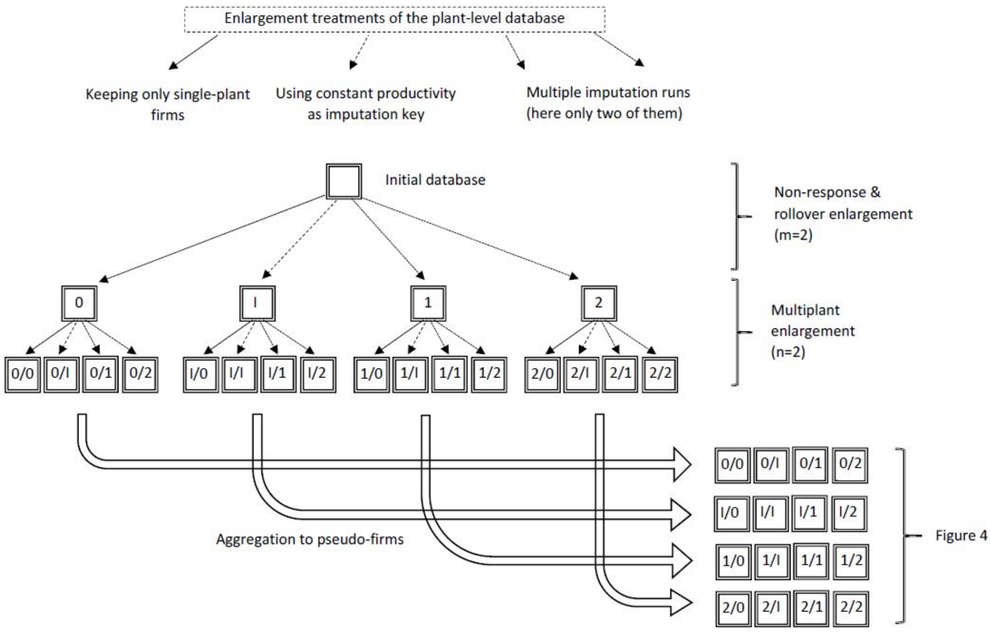
Taking the best out of available data sources, we used several techniques to address these caveats in a novel way. The new set of three databases that results includes consistent information on value added and employment at the level of pseudo-firms over the 2011-2015 period (a required aggregation, for confidentiality reasons, at the level of the municipality, legal form and 4-digit sector). Broadly speaking, our results are in line with the value added estimates produced by the FSO along an entirely different methodology. However, the composition of each sample is different, which must be kept in mind for interpretations.

For example, using National Accounts data suggests that Swiss productivity growth (in terms of value added per employee and for the subset of sectors considered in the WS survey) has been roughly equal to 0.6% per year across the 2011-2015 period. At the aggregated level, our three samples lead to larger figures for two of them (the restrictive sample, with 1% and the naive imputation sample, with 0.75%), and to a lower productivity growth for the multiple imputation sample (0.01% per year).

These differences reflect composition effects both between and within pseudo-firms. Limiting this final discussion to the multiple imputation sample (our preferred sample as it combines finely disaggregated measures of productivity with an appropriate level of representativeness), yearly productivity changes vary a lot across both municipalities (between -14% and +22%) and 4-digit sectors (between -11% and +22%). These structural patterns deserve further examinations in future studies.

Appendix A: Detailed imputation strategy in the m=2, n=2 case

Figure A.1: Detailed imputation strategy.



Appendix B: Geographic coordinates of a pseudo-firm: example

Figure B.1: Geographic coordinates of a pseudo-firm: example.

Red (blue) balloons correspond to the localization of the original firms (constructed pseudo-firm).

Appendix C: Weighted and non-weighted density functions

Figure C.1: Non-weighted density functions for full-time employment equivalents, all years.

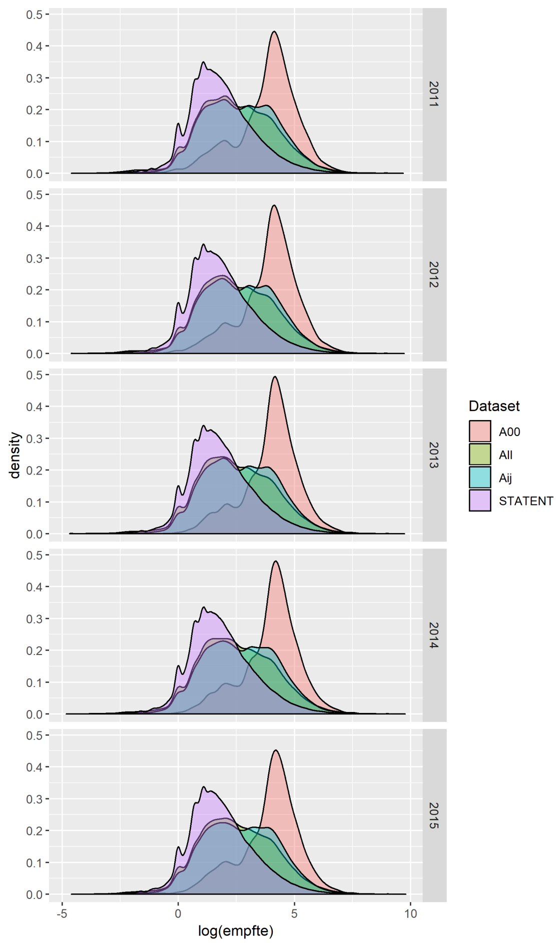


Figure C.2: Weighted density functions for full-time employment equivalents, all years.

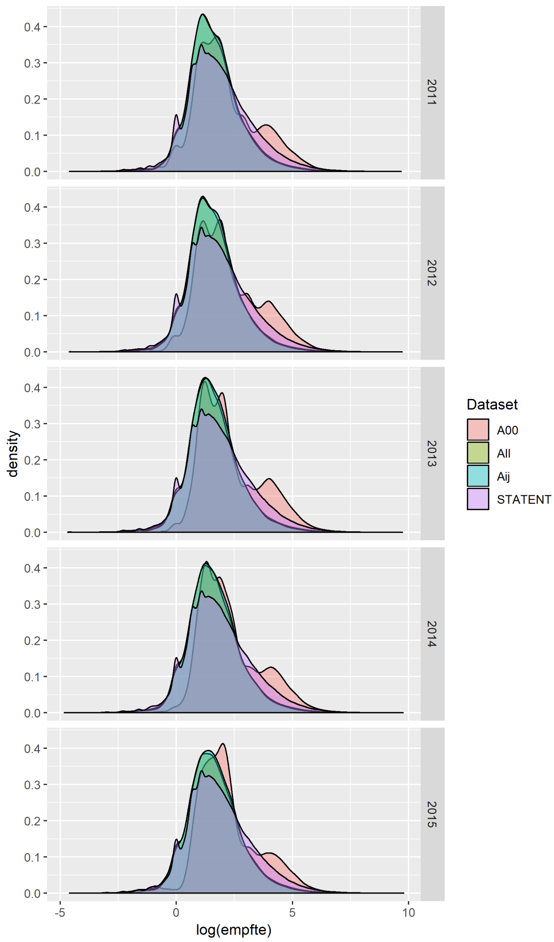
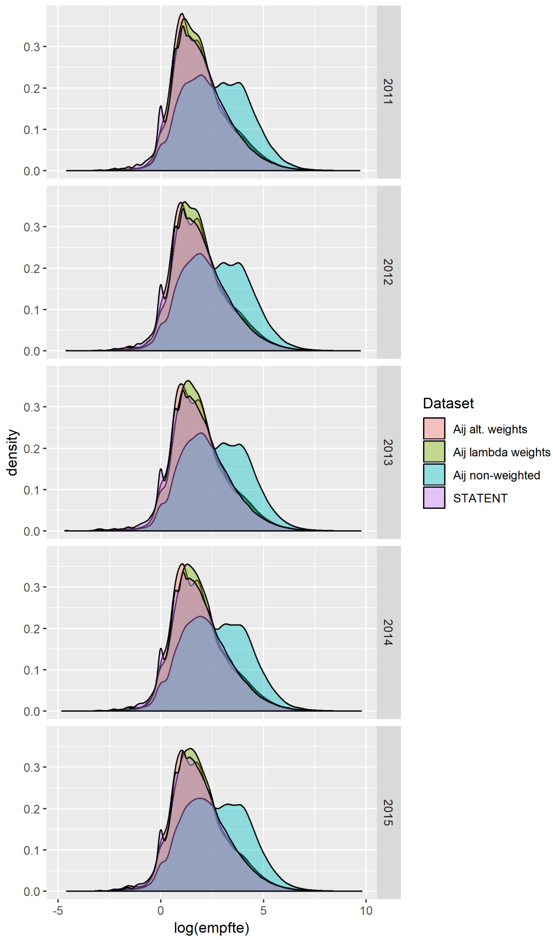


Figure C.3: Weighted and non-weighted density functions for Aij database, all years.



Appendix D: Recovering plant-level data employment figures: step 3

This appendix provides more details on step 3 of the general strategy to recover plant-level employment described in sub-section 3.3. For all pseudo-firms not covered by steps 1 and 2, the general principle is to apply a Gamma distribution first, then perform two further adjustments. The exact procedure is described below.

Applying the Gamma distribution assumption within pseudo-firms

We proceed as follows:

1. We infer the variance (V) of the pseudo-firm employment (X), $V = CV^2 \cdot \bar{X}^2$. Then we compute the shape (α) and rate (β) parameters of the Gamma distribution, $\alpha = \frac{\bar{X}^2}{V}$ and $\beta = \frac{\bar{X}}{V}$.
2. We divide the area below the Gamma pdf in n equi-probable intervals, with n being the number of plants in the pseudo-firm.
3. We consider the midpoint of each one of the first $n-1$ intervals as the estimated employment of the corresponding plant. We infer the n^{th} plant's employment by substracting from the pseudo-firm total employment the sum of the midpoint estimates found in point 3.

Adjusting the estimates obtained through the Gamma distribution

We define as a category the combination of year, municipality, NOGA4 and legal form that corresponds to each pseudo-firm. Within each category, we consider 20 size classes (see Figure 9). This allows refining the Gamma approximation avoiding two types of inconsistencies. More precisely, we reallocate FTE among plants of a given pseudo-firm in order to eliminate all cases where

- there is a plant in the sample for that category and size class, but no plant in STATENT. This would lead to attributing a weight of zero to that plant, i.e. a *zero-weight* size class.
- there are plants in both the sample and STATENT for that category and size class, but too many plants in the sample regarding total reported

FTE in STATENT. That is, even if FTE per plant was kept at a minimum in the sample (i.e. reduced to the lower bound of the size class for each plant), total FTE would remain larger in the sample. We call this an *overcrowded* size class.

Both problems signal that the Gamma-distribution-based attribution of pseudo-firm FTA across its plants is not correct. They also distort computed weights for the category and size-class and therefore deserve correction. The relative importance of both cases is presented in Table 3. A detailed presentation of each adjustment type follows.

Table D.1: Adjustments of the Gamma distribution estimates.

	Number of pseudo-firms	FTE	Average FTE per pseudo-firm	Share of pseudo-firms	Share of FTE
Elimination of zero-weight cases					
No zero weight	453	205404	91	0.5%	4.7%
Zero weight	710	326303	92	0.8%	7.5%
Elimination of over-crowded cases					
Not over-crowded	857	269089	63	1.0%	6.2%
Simple cases	251	192599	153	0.3%	4.4%
Non-simple cases	55	70016	255	0.1%	1.6%
Total	1163	531707	91	1.3%	12.2%

Adjustment procedure to eliminate the *zero-weight* cases

1. Identify MINS, the minimum size class with positive STATENT FTE figures and MAXS, the maximum size class with positive STATENT FTE figures.

2. Identify the number of plants with zero-weights. Classify them in three groups: UPGR = those with a size class smaller than MINS (must be lifted up), DWGR = those with a size class larger than MAXS (must be scaled down) and INGR = those with a size class in between MINS and MAXS.

3. If the UPGR is not empty, for each zero-weight case, identify the upward FTE gap, UPFG i.e. the extra FTE needed to reach the nearest larger

size class with employment in STATENT. Starting from the largest plant, attribute UPFG of extra FTE to the zero-weight plant while sharing the corresponding decrease in FTE on all other plants in proportion of their maximum capacity of provision under the constraint that they do not change size class. Repeat the procedure of the last sentence until the UPGR is empty.

4. If the DWGR is not empty, for each zero-weight case, identify the downward FTE gap, DWFG i.e. the decrease in FTE needed to reach the nearest smaller size class with employment in STATENT. Starting from the smallest plant, take away DWFG of FTE from the zero-weight plant while sharing it across all other plants in proportion of their maximum capacity of absorption under the constraint that they do not change size class. Repeat the procedure of the last sentence until the DWGR is empty.

5. If the INGR group is not empty, for each zero-weight case, compute the minimum of the upward and downward FTE gap as described in the previous two steps, i.e. MNFG=min(UPFG;DWFG). Rank these cases by increasing MNFG. Starting from the smallest MNFG, adjust the FTE of the zero-weight plant up (by UPFG) or down (by DWFG) depending on which adjustment is smaller and compensate that change across all other plants in proportion of their maximum capacity of absorption or provision under the constraint that they do not change size class. Repeat the procedure of the last sentence until the INGR is empty.

Adjustment procedure to eliminate the *over-crowded* cases

1. Identify all pseudo-firms that present one or more cases of over-crowded size classes.

2. Identify simple cases i.e. those where there is a single plant to relocate, either out of two or out of three plants in the corresponding category. For each simple case, identify the smallest amount of FTE that must be given to (or taken out of) the plant in order to shift it to the closest available size class.

3. For non-simple cases, attribute the required changes in FTE “by hand” i.e. printing the situation and finding the set of minimum changes in order to eliminate the over-crowded problem.

4. For both simple and non-simple cases, redistribute the net required FTE change (in order to maintain total FTE of the pseudo-firm unchanged) across all other plants in proportion of their maximum capacity of absorption or provision under the constraint that they do not change size class.

Table D.2: A_{00} coverage.

	Weigthed* full-time equivalent share	Weighted* value-added share†	Productivity ratio▽
Major regions			
Espace Mittlelland	100.1%	114.4%	114.3%
Région lémanique	74.0%	125.1%	169.2%
Zürich	69.7%	84.5%	122.1%
Nordwestschweiz	141.8%	177.0%	124.8%
Ostschweiz	130.1%	122.4%	94.0%
Zentralschweiz	107.3%	178.6%	166.5%
Ticino	106.2%	79.5%	74.9%
Industries††			
GHIJ	80.2%	166.5%	207.9%
BCF	190.1%	206.9%	108.9%
DEPQ	60.9%	82.7%	135.8%
LMNRS	65.5%	58.1%	89.0%
Total	100.0%	125.4%	125.4%

Notes:
† Share in value-added of the national accounts, excluding industries NOGA 1 A,K T and U, which are not covered by WS.
▽Ratio between average productivity in the sample and "national" productivity.
"National" productivity is based on own calculations using national accounts total value-added data and STATENT.
* Weights defined in section 3.2.
†† We exclude from the table sector O, which is not present in our sample.

Chapter 2

Zooming in the Swiss Low Productivity Puzzle: A Shift-share Analysis *

1 Introduction

Productivity growth is a key parameter in estimating national economic performance and its geographical distribution across domestic jurisdictions. It is of particular interest in a country like Switzerland, which combines a highly diversified industrial structure with a large variety of economic and social policies across cantons and municipalities. Besides, in spite of healthy economic conditions, Swiss aggregate productivity growth has been dismally low in recent decades. This has motivated a flurry of analyses, both at the macro and micro level.[1]

Unfortunately for the latter group of researchers, Swiss productivity data at the microeconomic level are almost impossible to find. A potential source of information is the value-added survey (Wertschöpfungsstatistik, WS) from the Federal Statistical Office (FSO), which provides yearly information on mone-

*This paper is co-authored by Jean-Marie Grether (University of Neuchâtel, Faculty of Economics and Business).

[1]We thank Nicole Mathys for her recommendations, and Sam Banatte, Markus Daeppen and Stephen Sonntag from the FSO for their data support. The usual disclaimers apply.

tary variables at the level of the production units. However, it does not allow to address directly productivity issues as it does not report employment figures. On top of that, the WS sample is limited to firm-level (not plant-level) data and it is biased towards large firms (more than 50 employees).

This paper exploits a novel database created by the matching between the WS survey and the yearly census of production units (STATENT database, FSO), which provides employment data. Moreover, as explained in a companion paper (Tissot-Daguette and Grether, 2019), multiple imputation techniques are used to enlarge the dataset towards smaller productive units. As a result, the enriched database we use in the present paper is both suitable for productivity analysis and more representative of the Swiss industrial structure than the WS survey.

We follow and extend simple decomposition techniques inspired from the shift-share analysis literature to characterize productivity performance across geographical units over the 2011-2015 period. In this framework, productivity growth can be explained by the combination of three structural forces, depending on the type of sectors (either incumbent, or emerging or absent in the given location) plus a competitive effect. Apart from providing interesting results for specific regions or cantons, the paper proposes a progressive "zoom" into the Swiss industrial landscape, first identifying general trends at the highest level of aggregation (7 major regions and 13 NACE+ categories), then extending the number of geographical units (26 cantons) or industrial sectors (460 NOGA4 sectors[2]).

The paper is structured as follows. Section 2 presents the literature background. Section 3 presents the growth rate decomposition method which is applied to value-added, employment and productivity figures. Section 4 comments the data and section 5 presents the basic results. An alternative database is discussed in Section 6 for robustness purposes and Section 7 concludes.

2 Literature Review

We provide some basic references on productivity estimates for Switzerland in recent years then present the fundamentals of shift-share analysis.

[2]Number of NOGA4 sectors present in our database over 615 NOGA4 sectors in total.

2.1 Empirical evidence

The low level of productivity growth in Switzerland has been a matter of debate since the 90s. Although early contributions were mostly macro-based (e.g. Brunetti and Zurcher (2002), Kohli (2005) or Siegenthaler (2015)), more recent studies have focused on firm-level evidence. This is in line with the ongoing international efforts to establish firm-level databases which are reliable and comparable across countries (e.g. the CompNet base for the EU, the firm-level projects of the OECD, or private sources like the FactSet or Orbis databases).

However Switzerland is either absent from these databases or its coverage is not satisfactory.[3] This is why, apart from studies on specific sectors[4] most authors have relied on two major sources of labour productivity at the level of the production unit: the Swiss Earnings Structure Survey (ESS) from the Federal Statistical Office (FSO) and the Swiss Innovation Survey (SIS) of the KOF Swiss Economic Institute of the ETH Zurich. In particular, the SIS has been used by Arvanitis et al. (2013) to provide an extensive analysis of labour productivity determinants at the firm and sector level over the 1990-2010 period, by Siegenthaler and Stucki (2015) to explain the surprising stability of the Swiss labour share of income in recent decades, and by Kaiser and Siegenthaler (2015) to analyse the slow productivity growth in knowledge-intensive business services. Marti et al. (2017) used the ESS to provide a thorough shift-share analysis of the variety of productivity growth patterns across Swiss regions. These studies have all contributed to identify sources of low productivity in Switzerland and the needs for corrective actions, as recently advocated by the Organisation for Economic Cooperation and Development (OECD, 2017).

In spite of these advances it is fair to say that the microeconomic basis to evaluate the fine patterns of productivity growth in Switzerland remains slim. The ESS database does not report measures for value-added, while the SIS database does not report full time equivalent and excludes firms with less than 5 employees. Meanwhile the low productivity problem persists, with macro measures (whether total factor productivity or labour productivity) suggesting that Swiss productivity growth has almost vanished since the big recession (e.g.

[3]See Ollivaud (2017), who mentions the notable exception of the STATENT database, which has allowed to perform interesting international comparisons (Mattmann et al., 2016), although excluding productivity measures as this database does not report information on monetary variables.

[4]e.g. Bolli and Farsi (2015) on Swiss universities, Lewrick et al. (2018) on manufacturing industries or Grass et al. (2017) on the pharmaceutical industry.

Tille (2018)). Thus, there is a need for further empirical evidence based on more comprehensive datasets, which is what the present study proposes.

2.2 Shift-share analysis

Shift-share analysis is a descriptive method, which aims to analyze regional performance (see Dunn, 1960; Fuchs, 1962; Ashby, 1964). It is widely used and discussed in the regional economics literature (see e.g. Erkus-Ozturk and Terhorst, 2018). The simplest form of this method decomposes the change in a variable in a specific location (typically employment of a given industry (Esteban-Marquillas, 1972), but also value-added (Oguz and Knight, 2010) or even energy demand (Otsuka, 2016)), into a national growth (NE), a industry-mix (or structural, SE) and a competitive effect (CE).

Let ΔX_{ij} be the change of employment in location j, in industry i, that occurs between two given time periods. The "classical" decomposition is as follow:[5]

$$\Delta X_{ij} = \underbrace{X_{ij} r}_{\text{NE}} + \underbrace{X_{ij}(r_i - r)}_{\text{SE}} + \underbrace{X_{ij}(r_{ij} - r_i)}_{\text{CE}}$$

where r is the national employment growth rate of growth, r_i the national employment growth rate of industry i, r_j region j employment growth rate and r_{ij} the region j employment growth rate in industry i. The contribution of the overall economy to the growth rate in the given location and industry is captured by the NE term. The contribution of the specialization of region j in sector i is given by the SE term, while the CE term captures the specific dynamism of region j regarding the growth rate in industry i.

This simple framework has been extended in several dimensions in the literature. Some have criticized the overlap between the CE and the SE effects in the original expression, as the X_{ij} part of the CE term also captures the industrial structure of the region. For this reason, Esteban-Marquillas (1972) and others have proposed to introduce further decomposition terms to allow for a better disentanglement between the CE and the SE effects. Others have focused on how best to capture the true dynamics of the underlying variable, discussing

[5] The notation is the one used in Mayor and López (2007). We abstract from period indices to simplify expressions.

the length of the time period over which growth rates are calculated, and the choice between the initial or the final employment levels (or still a combination of the two) in the above expression (e.g. Barff and Knight (1988), Selting and Loveridge (1994)). Another source of concern is to incorporate neighbouring effects, by allowing one region to influence another one in other ways than through the national average (e.g. Nazara and Hewings (2004), Mayor and López (2007)).

These refinements are worth considering in an in-depth analysis of the regional change of a single variable such as employment. In this paper our focus is on productivity, i.e. the ratio between two variables, and our firm-level database[6] allows considering various degrees of regional aggregation. This makes it more appropriate to stick to a standard SE-CE decomposition close to the original formula. As described in the next section, the extension we propose focuses on growth rates rather than changes in levels, and includes novel terms to capture the impact of new entrants or absent sectors in specific locations.

3 Methodology

We proceed in three steps, first adjusting the basic shift-share analysis expression to growth rates of employment and value-added, second extending it to account for new entrants and absent sectors, and third applying it to productivity growth.

3.1 Structural and competitive effects for growth rates

We assume first that region j is active (i.e. with positive levels of both employment and value-added) in all sectors across the sample period. Let us consider the growth rate of variable X (employment or value-added) either at the national level (r), or at the level of region j (r_j), or at the level of industry i, region j (r_{ij}). By definition, the national growth rate (r) is the X-weighted sum of regional growth rates (r_j, while the regional growth rate is the X-weighted sum of sectoral regional growth rates (r_{ij}). In other words we can write,

$$r_j = \sum_i (\frac{\theta_{ij}}{\theta_j}) r_{ij}$$

[6] "Firm" is here defined as an unique municipality/NOGA4/legal form combination.

$$r = \sum_i \theta_i r_i$$

where $\theta_{ij} = \frac{X_{ij}}{X}$ are the shares in the initial period, $X = \sum_j \sum_i X_{ij}$, $\theta_j = \frac{X_j}{X}$ and $X_j = \sum_i X_{ij}$. Taking the difference between the two above expressions, adding $\sum_i(\frac{\theta_{ij}}{\theta_j})r_i$-$\sum_i(\frac{\theta_{ij}}{\theta_j})r_i$ on the right-hand side and rearranging one gets

$$r_j - r = \underbrace{\sum_i (\frac{\theta_{ij}}{\theta_j} - \theta_i) r_i}_{SE_j} + \underbrace{\sum_i (r_{ij} - r_i)\frac{\theta_{ij}}{\theta_j}}_{CE_j} \tag{1}$$

where,

$\boldsymbol{\sum_i(\frac{\theta_{ij}}{\theta_j} - \theta_i)r_i}$ **is the structural effect (SE_j).** Abstracting from growth differences (i.e. $r_{ij} = r_i$), this indicates the contribution to growth of the industrial structure of region j. If this effect is positive, this means that the region is biased towards nationally growing sectors.

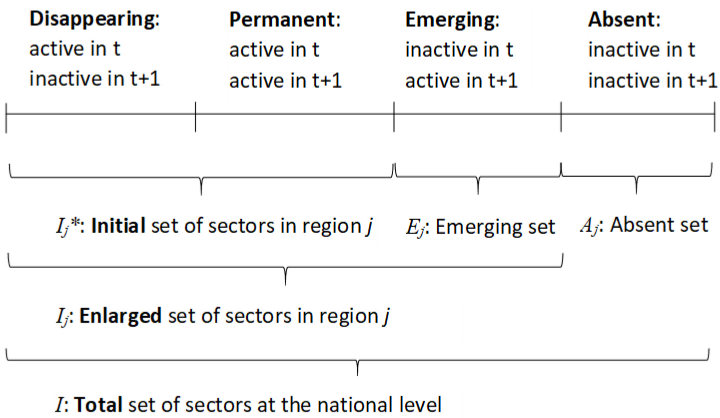
$\boldsymbol{\sum_i(r_{ij} - r_i)\frac{\theta_{ij}}{\theta_j}}$ **is the competitive effect (CE_j).** Abstracting from structural differences (i.e. $\frac{\theta_{ij}}{\theta_j} = \theta_i$), this is the contribution to growth of the regional growth rate of region j. If this effect is positive, this means that the region exhibits on average stronger growth rates than at the national level.

3.2 Accounting for absent and emerging sectors

To become operational, the above decomposition framework must be extended to account for the fact that some regions are only active in a subset of sectors and that this subset may change over time.[7] Figure 1 makes the crucial distinction between the *initial* set of active sectors in region j, I_j^*, and the *enlarged* set of sectors in region j, I_j, which includes the set of *emerging* sectors appearing in the second period, E_j, but which excludes those sectors that are *absent* both periods, A_j.

[7] We assume that, at the national level, all sectors are always active, which is what is observed in our sample.

Figure 1: Initial, enlarged and total sets of sectors



Note: To ease presentation, the **final** set of sectors in region j (enlarged set minus disappearing sectors) is not considered in the calculations.

Equation (1) only applies to the initial set of sectors, I_j^*, which is common to the regional and national level.[8] To apply it to the total set of sectors, I, we first introduce some notational conventions regarding growth rates, to highlight the geographic level of calculation (either region j or the nation) and the sector set involved (I_j^*, I_j, I, E_j, A_j).

At the regional level, $r_j(I_j)$ denotes the growth rate in region j on the enlarged set, while e.g. $r_j(I_j^*)$ denotes the corresponding growth rate on the initial set.[9] The same conventions apply to growth rates at the national level, e.g. total growth rate is written $r(I)$ or the national growth rate of absent sectors for region j, $r(A_j)$. Note that, by definition of absent sectors, we have $r_j(I) = r_j(I_j)$. Moreover, as the denominators of $r_j(I_j)$, $r_j(I_j^*)$ are identical while the numera-

[8]Strictly speaking this is not true, as we should also define a *final* set which excludes the disappearing sectors from the enlarged set. However, to simplify the decomposition formula, and as we consider only two periods in the analysis, we assume that the disappearing sectors are still there in the second period, but do not hire anybody nor produce anything.

[9]As usual, growth rates are obtained as the ratio between the final and the initial value minus one.

tor of $r_j(I_j)$ includes emerging sectors, we have always $r_j(I_j) > r_j(I_j^*)$.[10]

Using these notational conventions, we can now characterize the differences in growth rates between the total set (I) and the initial set (I_j^*) at both geographic levels:

At the level of region j**.** As $r_j(I){=}r_j(I_j)$, suffice is to define the *regional impact*, δ_j as $\delta_j \equiv r_j(I_j) - r_j(I_j^*)$. Note that, as discussed above $r_j(I_j) > r_j(I_j^*)$, so δ_j is necessarily positive.

At the national level . Both $r(I)$ and $r(I_j)$ can be expressed as a weighted average of their subcomponents i.e. $r(I){=}\theta_{A_j} r(A_j) + (1-\theta_{A_j}) r(I_j) = r(I_j) + \theta_{A_j}(r(A_j) - r(I_j))$ and $r(I_j){=}\theta_{E_j} r(E_j) + (1-\theta_{E_j}) r(I_j^*) = r(I_j^*) + \theta_{E_j}(r(E_j) - r(I_j^*))$, with $\theta_{A_j}(\theta_{E_j})$ representing the initial share of absent (emerging) sectors for region j in the national total. Combining these two expressions leads to $r(I) = r(I_j^*) + \theta_{E_j}(r(E_j) - r(I_j^*)) + \theta_{A_j}(r(A_j) - r(I_j))$.[11]

Replacing r_j $(=r_j(I_j^*))$ by $r_j(I_j)$-δ_j and r $(=r(I_j^*))$ by $r(I)$-$\theta_{E_j}(r(E_j) - r(I_j^*)) - \theta_{A_j}(r(A_j) - r(I_j))$ in Equation (1) and rearranging we obtain,

$$r_j - r = ASE_j + ESE_j + SE_j^* + CE_j^* \tag{2}$$

where $r_j \equiv r_j(I_j)$, $r \equiv r(I)$, $ASE_j = \theta_{A_j}(r(I_j) - r(A_j))$, $ESE_j = \delta_j - \theta_{E_j}(r(E_j) - r(I_j^*))$, $SE_j^* = \sum_{i \in I_j^*} \left(\frac{\theta_{ij}}{\theta_j} - \frac{\theta_i}{(1-\theta_{E_j} - \theta_{A_j})} \right) r_i$, and $CE_j^* = \sum_{i \in I_j^*} (r_{ij} - r_i) \frac{\theta_{ij}}{\theta_j}$ and θ_{E_j}.

In the above expression, the interpretations of the structural (SE_j^*) and competitive (CE_j^*) effects are similar to Equation (1).[12] The novelty comes from the two additional effects:

---

[10] This last inequality does not necessarily apply at the national level i.e. $r(I_j)$ may be larger, smaller or equal to $r(I_j^*)$.

[11] Note that a similar expression is not workable at the level of region j given that initial share of the set of emerging sectors in the regional total is zero and its growth rate infinite.

[12] Note that shares as θ_i are now defined on a larger total (including absent and emerging sectors i.e. $X_I = X_{I_j^*} + X_{E_j} + X_{A_j} = X_{I_j} + \theta_{E_j} X + \theta_{A_j} X$). Thus, when limiting the sum to I_j^* sectors, θ_i shares must be inflated by a $1/(1-\theta_{E_j} - \theta_{A_j})$ factor so that their total still leads to 1.

The absent sectors effect (ASE_j). The net impact of absent sectors on the growth gap of region j is proportional to the initial share of absent sectors at the national level (θ_{A_j}), and is positive (negative) if the absent sectors are lagging behind (running ahead) at the national level, i.e. if $r(I_j) > r(A_j)$ (if $r(I_j) < r(A_j)$).

The emerging sectors effect (ESE_j). The net impact of emerging sectors on the growth gap of region j is positive (negative) if their impact on the regional growth rate, δ_j^j, is larger (smaller) than their impact on the national growth rate, $\theta_{E_j}(r(E_j) - r(I_j^*))$.

3.3 Productivity growth decomposition

We first perform decomposition (2) on value-added and employment data. As the growth rate of a ratio is approximately equal to the growth rate of the numerator minus the growth rate of the denominator, it is tempting to assume that decomposition (2) simply applies by analogy to productivity growth, with each decomposition effect being equal to the difference between the corresponding effects for value-added and employment. However there is an error term and we have to slightly adjust the definition of the decomposition effects.

Let us denote value-added by V, employment by L and productivity by P. The value-added growth rates at the regional and national levels are given by:

$$\begin{aligned} r_j^P &= r_j^V - r_j^L - \epsilon_j \\ r^P &= r^V - r^L - \epsilon \end{aligned}$$

where $\epsilon_j = (r_j^V - r_j^L)(\frac{r_j^L}{1+r_j^L})$ and $\epsilon = (r^V - r^L)(\frac{r^L}{1+r^L})$ are the error terms. By subtracting the two expressions we get,

$$r_j^P - r^P = (r_j^V - r^V) - (r_j^L - r^L) - (\epsilon_j - \epsilon)$$

In the above expression, we substitute $r_j^V - r^V$ and $r_j^L - r^L$ by their respective decompositions and spread the combined error term homogeneously across the decomposition effects to obtain,

$$r_j^P - r^P = ASE^P + ESE^P + SE^{*P} + CE^{*P} \tag{3}$$

where $ASE^P = (ASE^V - ASE^L) - (\frac{1}{4})(\epsilon_j - \epsilon)$, $ESE^P = (ESE^V - ESE^L) - (\frac{1}{4})(\epsilon_j - \epsilon)$, $SE^{*P} = (SE^{*V} - SE^{*L}) - (\frac{1}{4})(\epsilon_j - \epsilon)$, and $CE^{*P} = (CE^{*V} - CE^{*L}) - (\frac{1}{4})(\epsilon_j - \epsilon)$.

4 Data

We first describe the origin of the datasets used to decompose productivity growth. Then we comment the overall trends of employment and value-added growth across the 2011-2015 period.

4.1 Data sources

We match two data sources from the Federal Statistical Office over the period 2011-2015, the employment data from the STATENT census (Statistique Structurelle des Entreprises) and the value-added data obtained from the WS survey (Wertschöpfungsstatistik). The WS survey is at the firm level, excludes the primary sector and the banking and financial services sector, and is limited to firms with three or more employees. Small firms (below 50 employees) are sampled according to sectoral and size categories, and remain in the sample for five years only. Combined with non-response and the necessity to aggregate the data at the level of pseudo-firms (i.e. a given combination of NOGA-4digit sector, municipality and legal form) for confidentiality reasons, these characteristics make it particularly challenging to ensure that the final sample is sufficiently representative of the whole population.

We address these issues into detail in Chapter 1. Our basic strategy is to construct two types of samples. On the one hand, a *restricted* sample is obtained by trimming out all firms that are replaced, do not respond, or regroup establishments spread across pseudo-firms (i.e. municipality-sector-legal form combinations). This considerably reduces the size of the sample, to less than 3'000 observations per year (starting from around 22'000 initial observations per year in the WS survey). The matching with the distribution of employment in the whole (STATENT) population is imperfect, and the representativeness of the *restricted* sample is therefore limited. On the other hand, we construct a series of *imputed* samples using either proportionality conventions (*naive* imputations) or econometric techniques (*multiple* imputations). Both imputation routes allow to avoid losing information from the original survey and achieve a far better matching with the whole population. The *naive* imputation route is not appropriate in the context of the present paper as the basic assumption to reconstruct missing data is that productivity remains constant over years or over establishments of the same firm. Thus, we will focus here on the databases obtained through multiple imputation techniques, which account for a bit less than 18'000 observations per year and are more representative of the entire population of Swiss firms than the *resricted* sample.[13] As there are 20 runs of imputations performed to address two sources of missing data (first rollover and non-response of small firms, second multiplant spreading), this leads to 400 different imputed datasets per year. We report here the average results across these 400 datasets and a confidence interval based on their standard deviation.

In order to simplify the presentation of results, the main text will focus on aggregate results obtained from the *imputed* sample on average over the 2011-2015 period, for the seven large regions and thirteen NACE+ sectors. Unless otherwise specified, all calculations involve weights so the identified patterns apply to the population as a whole, not only the selected samples. Results at the NOGA4 classification level, for cantons and for the *restricted* sample are discussed subsequently. Yearly results are reported in the Appendix.

4.2 Broad trends in employment and value-added

Unless otherwise specified, when calculating growth rates, we consider the average over the 2011-2012 (2014-2015) sub-period as the initial (final) value. This allows smoothing out short run fluctuations. Figures are then converted into yearly equivalents.[14]

Table 1 reports the initial shares and yearly growth rates of employment (full-time equivalent) and value-added for large regions and broad industrial categories.[15]

[13]See the companion paper for descriptive statistics on the alternative datasets obtained.

[14]In the particular case of decomposition formulas (2) and (3), we start calculating for each element the overall growth rate over the whole 2011/12-2014/15 period. This satisfies precisely each equality. Then we consider the net growth rate on the left-hand side and annualize it. Each element on the right-hand side is then adjusted in the same proportion as the left-hand side net decrease.

[15]Large regions are those defined by the Federal Statistical Office. Large sectors are based on the nine NACE+ categories where categories 2a (manufacturing industries) and 4 (services) have been split into subcategories as they jointly represent around two-third of employment.

Table 1: Large regions and large sectors in Switzerland

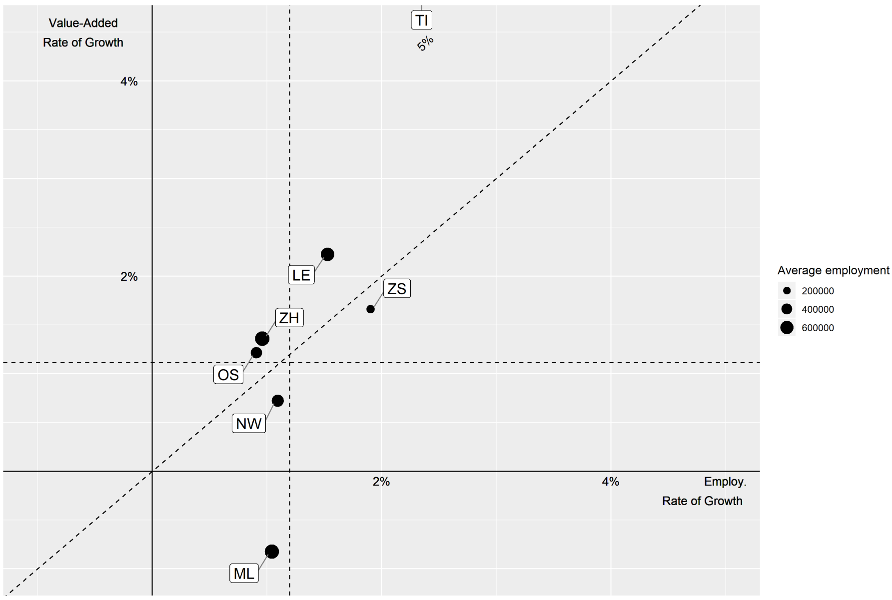
Code	Name	2011-2015 Share			Average growth 2011-2015	
		Pseudo-firms	Employment	value-added	Employment	value-added
ZH	Zürich	15.3%	22.5%	22.6%	0.96%	1.36%
ML	Espace Mittelland	21.0%	18.8%	19.4%	1.04%	-0.82%
LE	Région lémanique	18.5%	22.4%	21.1%	1.53%	2.22%
NW	Nordwestschweiz	15.4%	17.7%	19.7%	1.09%	0.72%
OS	Ostschweiz	16.6%	13.0%	10.4%	0.91%	1.21%
ZS	Zentralschweiz	9.7%	6.7%	5.7%	1.90%	1.66%
TI	Ticino	2.4%	2.9%	2.4%	2.35%	5.01%
41	Whole and retail sales	21.8%	17.6%	23.7%	0.50%	0.77%
2a3	Metal and machines manufacturing industries	13.7%	16.9.2%	17.5%	-0.89%	0.37%
8	Scientific and technical activities, administrative services	12.8%	14.2%	12.9%	2.42%	3.03%
3	Building sector	8.0%	11.9%	9.4%	1.95%	1.98%
9	Public administration, defense, teaching, health and social activities	7.5%	6.6%	3.5%	6.10%	3.51%
43	Accomodation and food services	3.5%	6.5%	3.3%	1.71%	0.33%
2a1	Food, textiles and wood manufacturing industries	8.4%	5.8%	5.6%	-0.32%	-2.37%
42	Transport and storage	4.7%	5.6%	5.1%	0.36%	0.70%
44	Communication and information services	5.3%	5.2%	6.7%	0.73%	1.99%
2a2	Chemicals and Pharmaceuticals manufacturing industries	4.4%	5.0%	8.8%	0.10%	1.38%
10	Other services	5.4%	2.7%	1.5%	3.58%	2.29%
7	Real estate	3.2%	1.6%	1.5%	2.19%	3.03%
2	Extraction and other industries	1.3%	0.4%	0.4%	2.59%	1.70%

To ease interpretation, growth rates are plotted in Figure 2 (for regions) and Figure 3 (for sectors). Horizontal and vertical dotted lines in both figures represent national average growth rates, and the location of a dot above (below) the 45 degree line indicates an increase (decrease) in productivity over the sample period for that particular region or sector.

A striking feature for regions is that they are very homogeneous in terms of employment growth rates, as most dots are vertically aligned along the national growth rates of slightly more than 1%, with the notable exceptions of Zentralschweiz and Ticino (around 2%). The variance is a lot stronger for value-added, with extreme cases represented by Ticino (5%) and Mittelland (less than -1%). Between these extremes, productivity increases in Zurich, Région lémanique and Ostschweiz, and decreases in Nordwest and Zentralschweiz. Section 5 below will help us to understand what hides between these contrasted results.

The overall picture for large sectors is different, with the majority of sectors pretty much aligned along the diagonal, which means a productivity that

Figure 2: Average growth of employment and value-added by major regions 2011-2015.

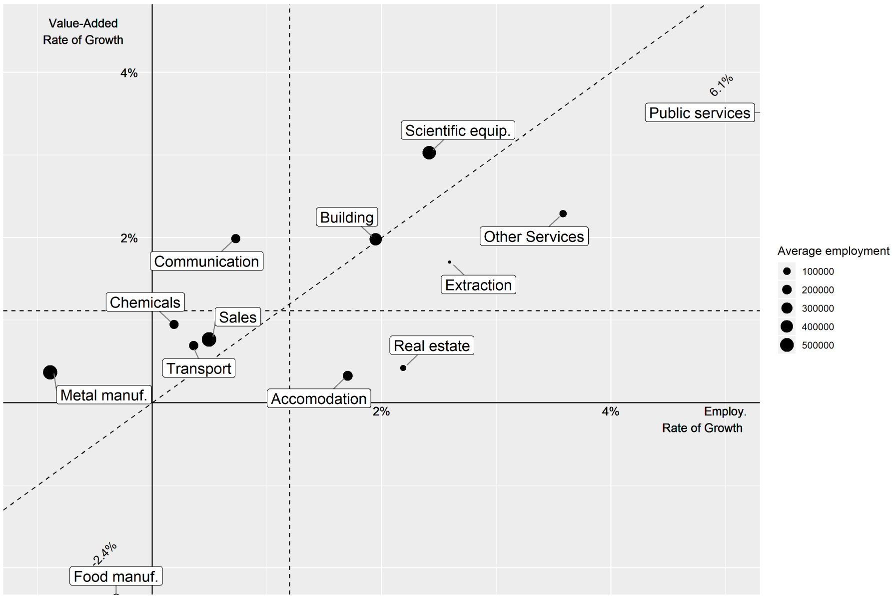


Note: Annual growth over the 2011-2015 period; employment measured in full time equivalents; the size of dots is proportional to the average regional employment; see Table 1 for names of (and basic statistics on) major regions.

remains quite stable on average. Sectors with decreasing productivity are basically Food, Textiles and Wood (with a decrease of around -2% in value-added and almost stable employment), and Public administration (with an increase of +6% in employment which is not matched by a corresponding increase in value-added). Conversely, Scientific equipment, Communication and Information, and Chemicals and Pharmaceuticals do exhibit an increase in productivity.

These average trends over the whole period may hide important year-to-year differences. Figure 4 reports five maps of productivity growth for Switzerland. The far-right panel, which covers the whole 2011-2015 period, confirms the patterns identified in Figure 1, with a strong increase in productivity for Ticino

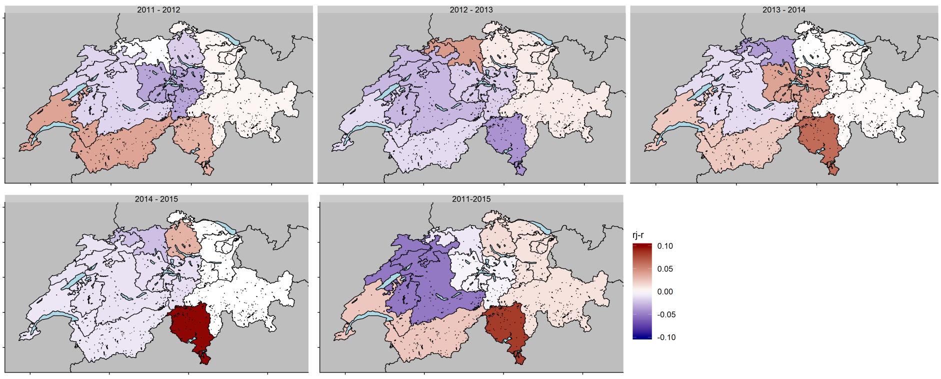
Figure 3: Average growth of employment and value-added by large sectors 2011-2015.



Note: Annual growth over the 2011-2015 period; employment measured in full time equivalents; the size of dots is proportional to the average industrial employment; see Table 1 for detailed names of (and basic statistics on) major sectors.

and a decrease for Mittelland. However, the other four panels show that results may change quite importantly from one year to the other, as often discussed in the literature (e.g. Selting and Loveridge (1994)). This is why we generally complement the results by yearly indicators in the Appendix.

Figure 4: Regional productivity growth in Switzerland 2011-2015.



Note: Growth rate of the average value-added per full time equivalent in each major region; annual equivalent for the 2011-2015 period.

5 Results

We discuss the results of the shift-share decomposition exercise combining two types of figures.

Two-dimensional plot diagrams. These plots allow to identify at a single glance the main sources of employment growth (or value-added, or productivity) along the lines of expression (2). More precisely, we report on the horizontal axis the sum of the first three terms (ASE, ESE and SE*) and call this sum the (combined) *structural* effect, while we report the CE* term on the vertical axis, representing the *competitive* effect. This is done in Figures 5 (employment), 6 (value-added) and 7 (productivity), which also reports the negatively sloped 45-degree line as a reference locus. Any point above (below) that diagonal indicates a positive (negative) growth differential with respect to the national average, and the larger the orthogonal distance from the diagonal, the larger the absolute growth differential.

Bar-diagrams. The second type of figures are bar-diagrams presenting precisely the detailed decomposition of expression (2) namely the growth differential $(r_j - r)$, the absent sectors effect (ASE), the emerging sectors effect (ESE), the (pure) structural effect (SE*) and the competitive effect (CE*). These more precise diagrams also report the national growth rate (r) and a confidence interval derived from the 400 imputed datasets. Figure 8 reports the average results for employment, value-added and productivity over the whole sample period 2011-2015, while year-to-year results are reported in Figures A.1, A.2 and A.3 in the Appendix.

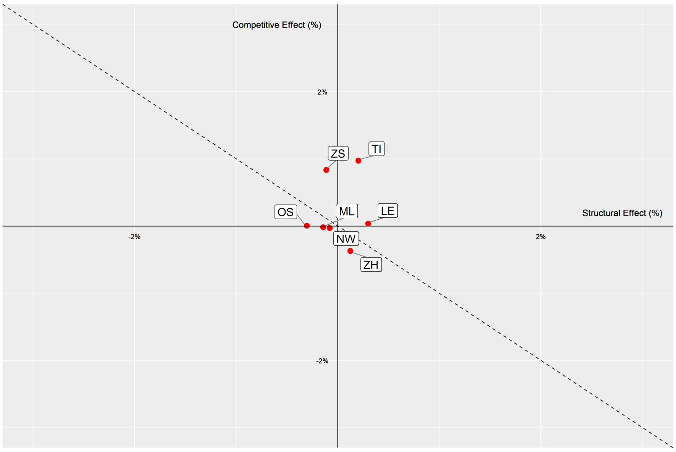
For each one of the three variables, the logic of the discussion is to start with the quicker-to-read two-dimensional plot and then look at the bar-diagram figure for more in-depth explanations of the observed patterns. We first discuss the results for major regions, then report and comment results at the cantonal level.

5.1 Results for major regions and NACE+ sectors

Starting with employment, Figure 5 suggests that effects are rather small (dots are close to the origin) and that most regions have a small differential with respect to the national average (distance to the dotted line). The only regions that stay apart from that pattern are Ticino and Zentralschweiz, with a CE around 1%. This is confirmed by the upper panel of Figure 8, which also shows that the (weak) negative SE effects for Northwestschweiz and Espace Mitteland are due to a "pure" structural effect, as the ESE and ASE terms are zero at this level of aggregation. In short, employment growth has been low and homogeneous across regions. The exception comes from Ticino and Zentralschweiz where the positive differential is mainly due to the dynamism of those specific regions. A look at Figure A.1 in the Appendix suggests that the first (2011-2012) and the last subperiod (2014-2015) are the main drivers of that specific pattern in Zentralschweiz, while they consist of subperiods (2012-2013) and (2013-2014) in Ticino.

Results are more contrasted for value-added. Figure 6 shows roughly three different groups: first, low-growth differential regions, close to the origin (Zurich, Nordwest and Ostschweiz), second a group of three major regions with a weak structural effect but a large competitive one, either positive for Zentralschweiz and Région lémanique or negative for Mittelland; and third an outlier represented by Ticino, with a strong competitive effect. This pattern is confirmed by the middle panel of Figure 8, which shows that the larger growth achieved by Région lémanique with respect to Zurich is mostly due to its strong competitive

Figure 5: Structural+competitive effects, employment, regions 2011-2015, NACE+.

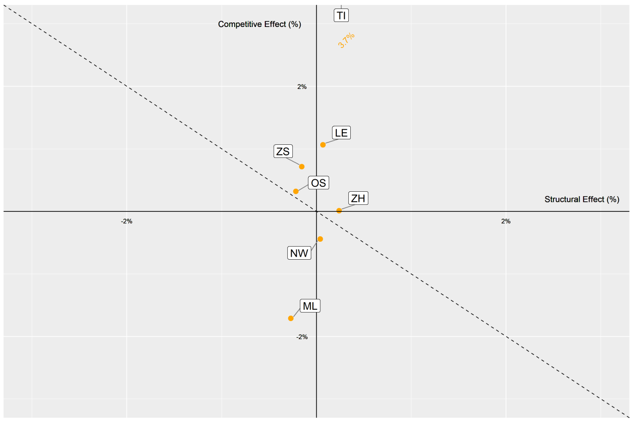


Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

effect, while Zurich relies on a (pure) structural effect. These average patterns over the whole sample period hide important variations across years as illustrated by Figure A.2 in the Appendix. It shows for example that the relatively small net change for Nordwestschweiz is the combination of a sharply positive differential in 2012-2013 followed by opposite negative ones in 2013-2014 and 2014-2015. Overall, the competitive effect is the main driver of the net outcome.

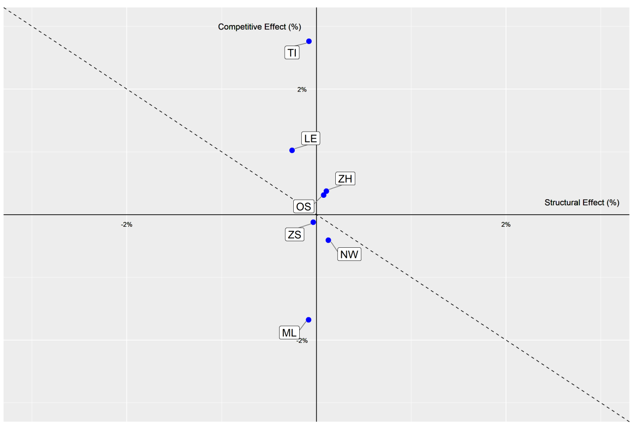
As differential growth effects are smaller for employment than for value-added, it is expected that the decomposition results for productivity will broadly mimic the value-added ones. Figure 7 (or the lower panel of Figure 8) confirms that this is the case, with a pattern which is very similar to Figure 6 (or the middle panel of Figure 8). There are three differences however. First, the national productivity growth (r) is slightly negative. Second, the growth differential is now similar for Zurich and Région lémanique, due to differences in employment growth (negative for the former, positive for the later). Third, Zentralschweiz exhibits a negative differential, because employment growth has been larger than value-added growth. Here again, Figure A.3 in the Appendix confirms strong year-to-year variations.

Figure 6: Structural+competitive effects, value-added, regions 2011-2015, NACE+.



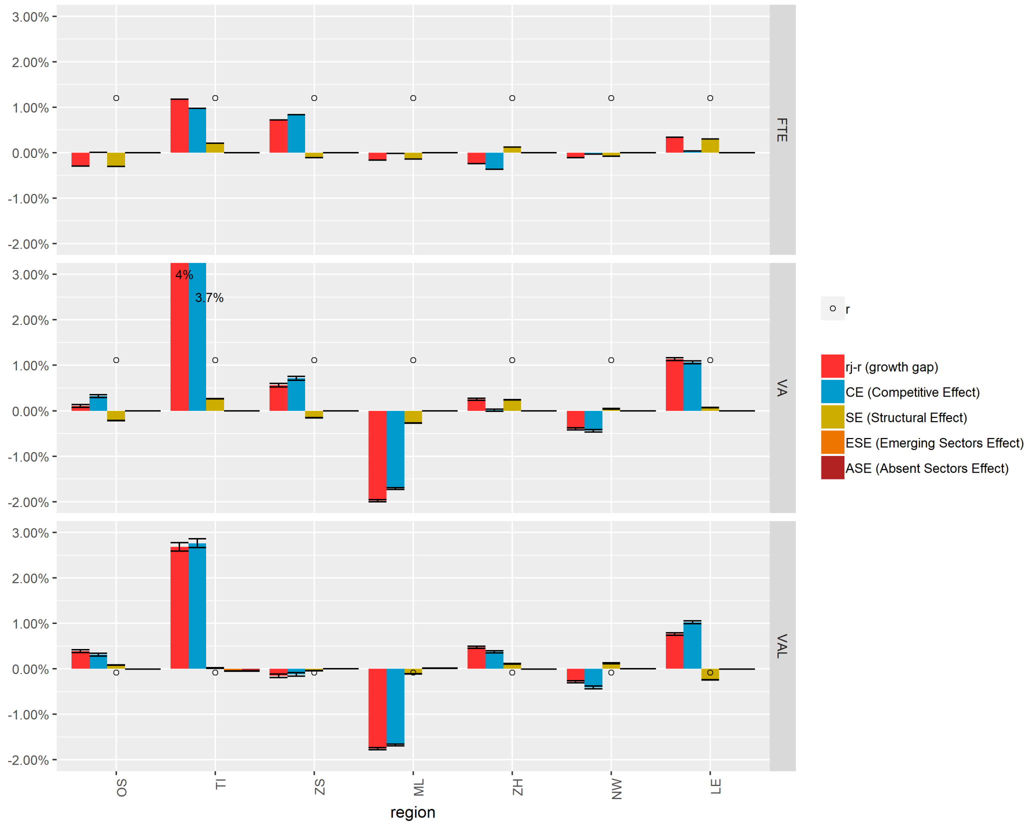
Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

Figure 7: Structural+competitive effects, productivity, regions 2011-2015, NACE+.



Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

Figure 8: Detailed decomposition for employment, value-added and productivity, major regions 2011-2015, NACE+ sectors



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "○" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples.

5.2 Results for major regions and NOGA4 sectors

The weak structural effects identified so far are probably due to the fact that thirteen NACE+ sectors are too few to reveal important structural differences between regions. What constitutes "machine manufacturing" firms in the Mittelland may be different to what they are in, say Ticino or Région lémanique. Thus, "zooming in" i.e. going further down the industrial classification may unveil differences across regions, which is why we report below results obtained by replacing the NACE+ by the NOGA4 industrial classification (460 sectors, see Figure B.4 in the Appendix).

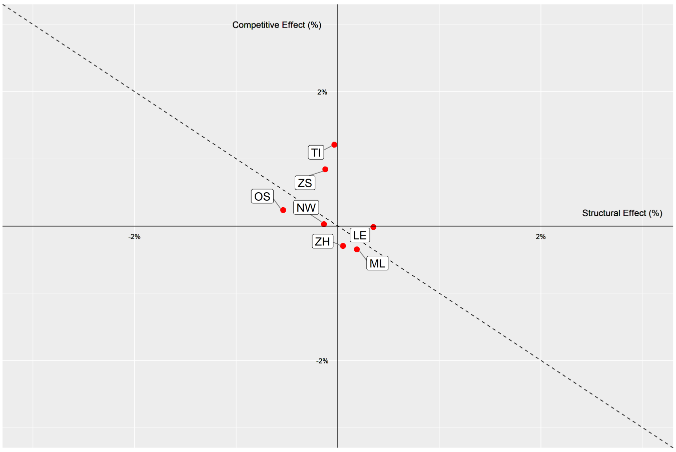
At first sight, the impact of that change is negligible, at least regarding employment. Most dots in Figure 9 (NOGA4) are at the same location as in Figure 5 (NACE+). However, this is not true for value-added. In Figure 10, apart from Ticino which remains an outlier, most dots are now more evenly spread horizontally in comparison to Figure 6. Structural effects are now non-negligible, either positive as in Zurich and Nordwestschweiz, or negative as in Zentralschweiz, Mittelland and Région Lémanique. For the same reasons as previously discussed, the pattern for productivity growth is very similar (see Figure 11).

Overall, the productivity growth pattern that emerges looks different now. While most of it was attributed to the competitive effect while working at the NACE+ level (dots aligned along the vertical axis in Figure 11), both types of effects seem to matter when using NOGA4 sectors (dots more evenly spread in Figure 7). Of course the orthogonal distance to the downward-sloping diagonal, i.e. the net total effect, remains identical between the two diagrams, but the contributions of the two effects to that distance are now more varied. In short, it seems that zooming in the industrial structure has allowed to explain part of the competitive effects identified at the aggregate level.

Figure 12 presents the decomposition of the three elements constituting the gross structural effect discussed above (see Equation (2)). As it turns out, apart from Ticino where they play a relatively minor role, the impact of the emerging sectors (ESE) and absent sectors (ASE) effects on productivity growth appears negligible. Most of the variation can thus be attributed to the "pure" structural effects affecting the incumbent sectors.[16] However, this may be due to the fact

[16] Apart from a few exceptions, this remains true when working on year-to-year variations, see Figures B.1, B.2 and B.3 in the Appendix

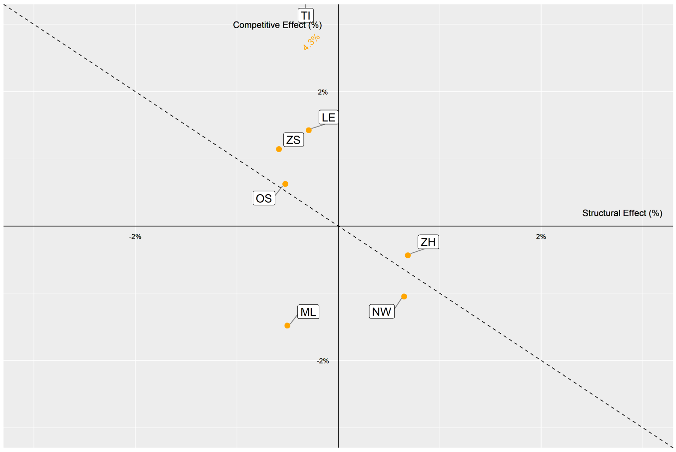
Figure 9: Structural+competitive effects, employment, regions 2011-2015, NOGA4.



Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

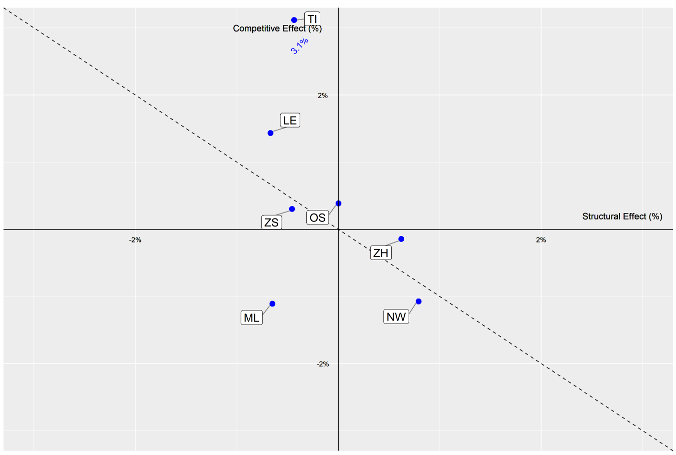
that regions are so large that even when working at the NOGA4 level, all sectors are present in all regions and all years. This may not be the case anymore when working with smaller geographical areas like cantons, which is what the next subsection analyses.

Figure 10: Structural+competitive effects, value-added, regions 2011-2015, NOGA4.



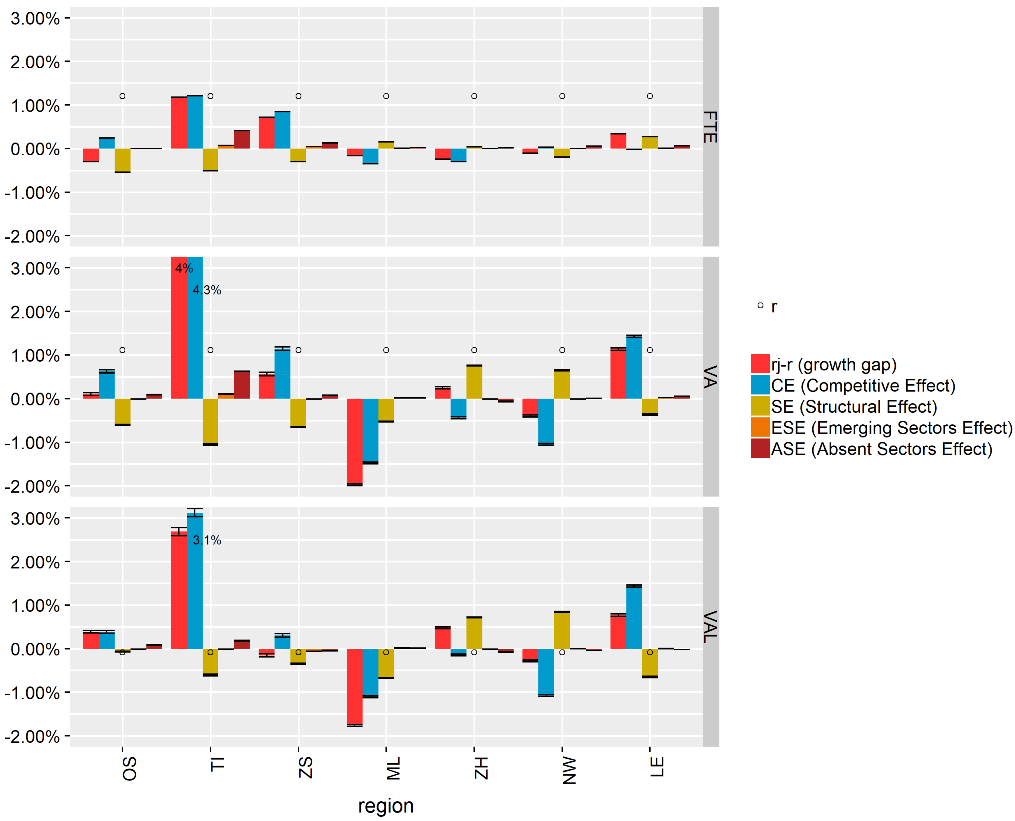
Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

Figure 11: Structural+competitive effects, productivity, regions 2011-2015, NOGA4.



Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

Figure 12: Detailed decomposition for employment, value-added and productivity, major regions 2011-2015, NOGA4 sectors.

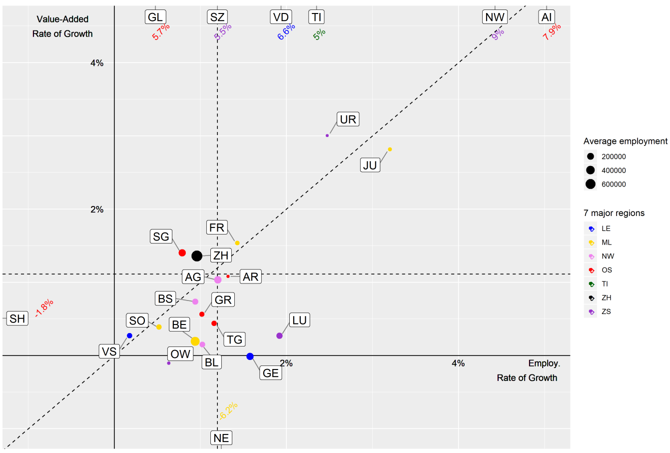


Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples.

5.3 Results for cantons and NOGA4 sectors

Figure 13 provides the scatter plot for employment and value-added growth at the level of cantons over the 2011-2015 period. The general picture is similar to what is obtained at the level of major regions (see Figure 2) i.e. most dots seem vertically aligned along the sample mean. Apart from the specific cases of Ticino and Zurich, the only major region which seems homogeneous is Nordwestschweiz, with Aargau, Baselstadt and Baseland locating close to one another. All other major regions present sharp contrasts between the highest growing canton (Fribourg, Vaud, Appenzell Innerrhoden and Nidwald) and the lowest growing canton in terms of value-added (Neuchâtel, Geneva, Thurgau and Luzern).

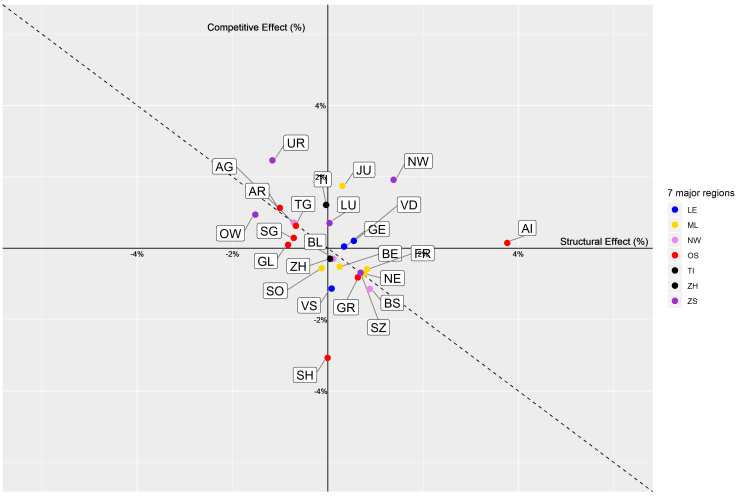
Figure 13: Average growth of employment and value-added by cantons 2011-2015.



Note: Annual growth over the 2011-2015 period; employment measured in full time equivalents; the size of dots is proportional to the average cantonal employment.

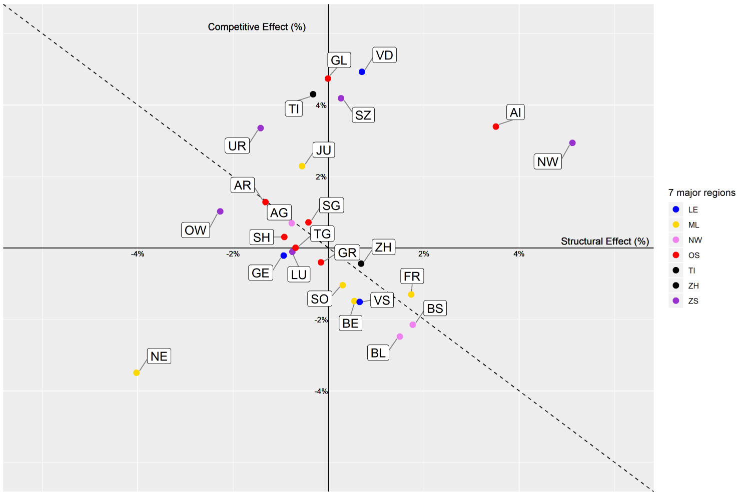
The SE-CE decomposition applied to employment, value-added and productivity leads to overall figures (see Figures 14, 15 and 16) which are similar in shape to those obtained above that is, rather low SE effects for employment, but larger ones for value-added and productivity. The order of magnitude is larger, as could be expected given the observed heterogeneity within major regions. In particular, the highest productivity growth is found in Schwiz, Vaud and Glarus (around +5%) and the lowest is experienced by Neuchâtel (around -7%).

Figure 14: Structural+competitive effects, employment, cantons 2011-2015, NOGA4.



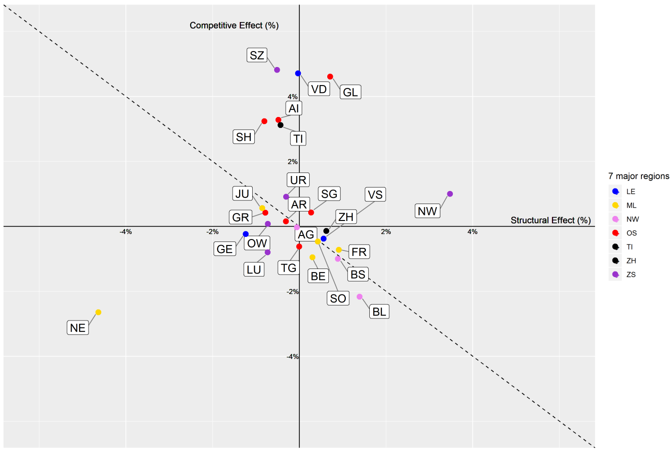
Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

Figure 15: Structural+competitive effects, value-added, cantons 2011-2015, NOGA4.



Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

Figure 16: Structural+competitive effects, productivity, cantons 2011-2015, NOGA4.



Note: The horizontal axis regroups the SE, ESE and ASE terms of equation (2) in the main text, the vertical axis represents only the CE term.

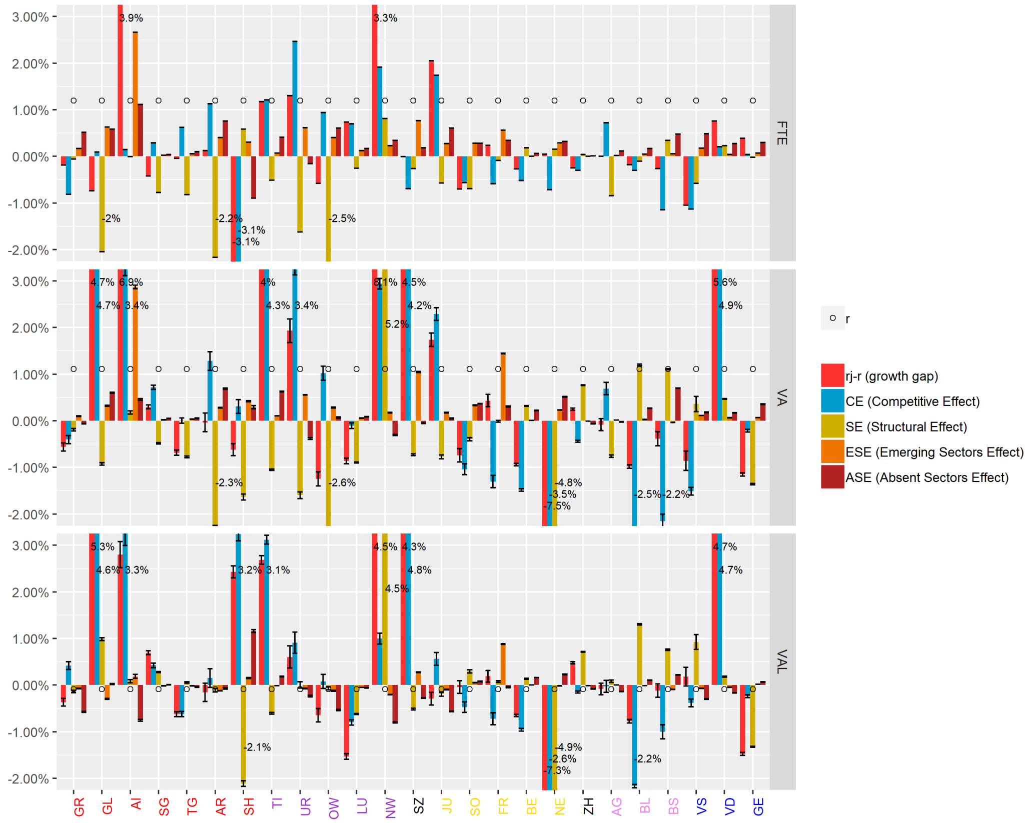
The structural effects that appear in the plot diagrams are underestimates of the true structural forces at work, given that they collapse the three effects described in equation (2) into a single term. Figure 17 provides the decomposition into the three components. In several instances, there are strong compensations between the three effects.

For example, for employment growth in Glarus (and to a lesser extent in Appenzell Ausserrhoden), the "pure" structural on incumbent sectors (SE) is strongly negative (around -2%) but it is almost perfectly matched by the positive impact of emerging and absent sectors (ESE and ASE effects). The opposite occurs for employment growth in Schaffhausen, where the positive pure SE effect is almost matched by the negative ASE effect. In the case of Fribourg, the contribution of incumbent sectors on productivity growth is negative, and compensated by the positive impact of emerging sectors.

Overall, and as expected, the structural effects turn out to matter more when using cantons rather than major regions.[17] Even if the competitive effect remains the dominant force in certain cases (e.g. the strong productivity increase for Ticino and Schwyz), it becomes less prevalent in other cases (e.g. in Neuchâtel, where structural forces regarding incumbent and emerging sectors combine to generate a strong productivity decline).

[17] See also their importance in year-to-year variations in Figures C.1, C.2 and C.3 in the Appendix)

Figure 17: Detailed decomposition for employment, value-added and productivity, cantons 2011-2015, NOGA4 sectors.



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples. Cantons sorted in ascending average productivity order in each given major region (colored).

6 Alternative data sample

A final set of results is obtained using the alternative *restricted* sample described in section 4. As above mentioned, this sample is less representative of the whole population of Swiss firms, with around six times less observations and a bias towards large single plant firms. It should come as no surprise if results turn out to be different, which they do. As patterns are already different at the most aggregated level (major regions and large sectors) we limit the discussion to that case.

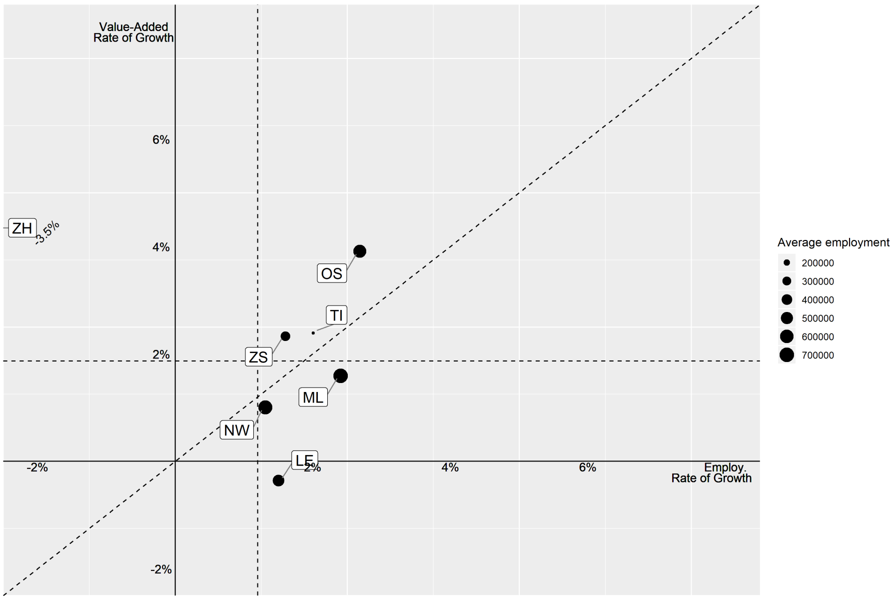
Figures 18 and 19 present growth rates for employment and value-added either for regions or sectors, and should thus be compared to Figures 2 and 3. The overall pattern of dots rather aligned vertically for regions and along the diagonal for sectors remains broadly unchanged, so for that sample also we should expect that region-specific competitive effects dominate over structural effects, as can be verified looking at Figure 20.

However, apart from theses general similarities, there are a number of differences. First, the overall growth rate for value-added is almost twice as large, while the growth rate for employment is similar, Therefore, based on the restricted sample, on average there is an increase (slightly less than 1%) in productivity in Switzerland, contrasting with the small decrease (around -0.2%) discussed for the imputed sample.

Second, important differences appear between regions. Ticino loses its outlier status. The outlier is now Zurich, with a strong productivity increase due to both an increase in value-added and a decrease in employment. In total contrast with the imputed sample, Région lémanique and Ticino now exhibit a productivity decrease while productivity slightly increases in Zentralschweiz. Year-to-year differences are also important (see Figures D.1, D.2 and D.3 in the Appendix).

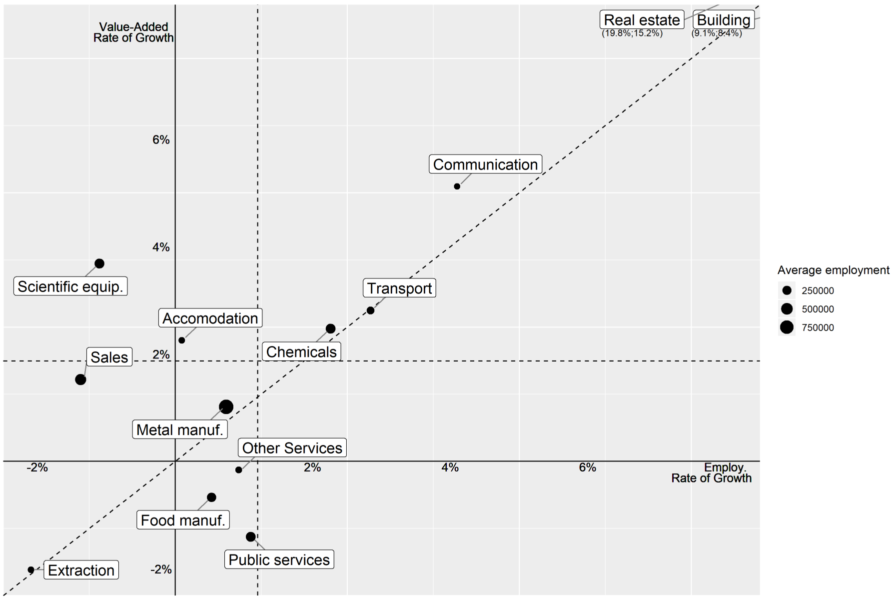
Third, there are also some differences for sectors. In general, the sign of the productivity growth rate remains unchanged (apart from Accommodation and food services and Real estate where productivity increases). However, there are important differences in the magnitude of employment growth, which becomes very large for the Building and Real estate sectors.

Figure 18: Average growth of employment and value-added by major regions 2011-2015 (restricted sample).



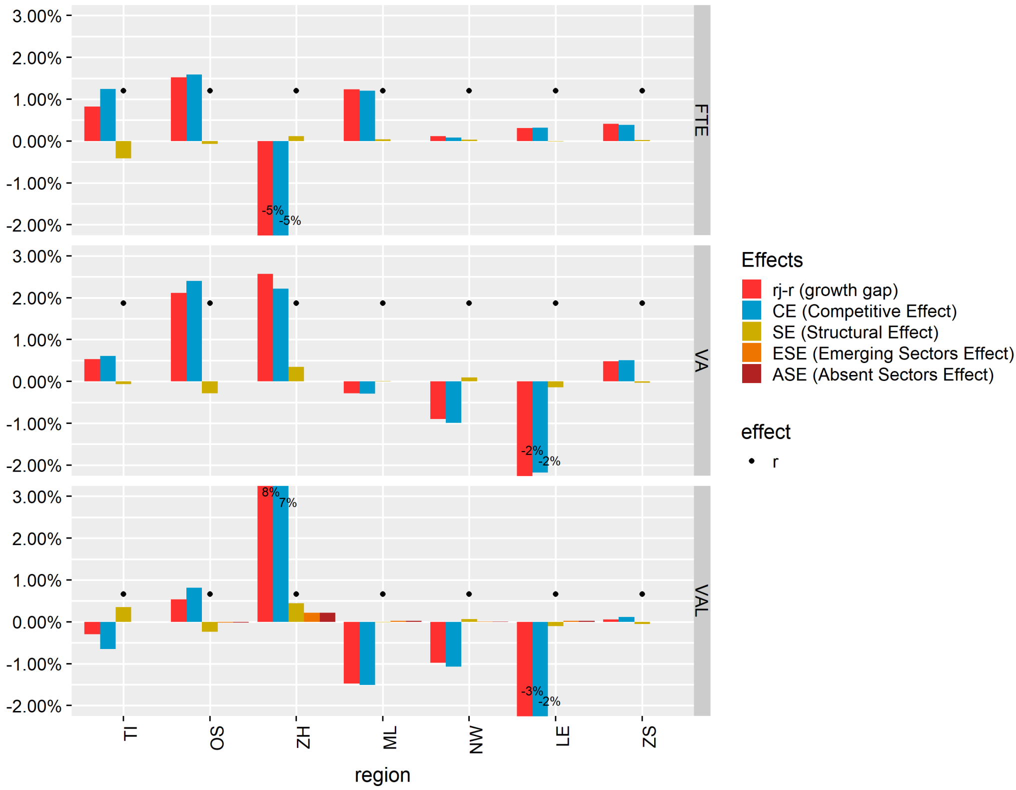
Note: Annual growth over the 2011-2015 period; employment measured in full time equivalents; the size of dots is proportional to the average regional employment; see Table 1 for names of major regions.

Figure 19: Average growth of employment and value-added by major sectors 2011-2015 (restricted sample).



Note: Annual growth over the 2011-2015 period; employment measured in full time equivalents; the size of dots is proportional to the average industrial employment; see Table 1 for names of major sectors.

Figure 20: Detailed decomposition for employment, value-added and productivity, major regions 2011-2015 (restricted sample).



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "$\circ$" character represents the national average (r).

7 Conclusion

On the basis of a shift-share analysis of productivity growth applied to a novel database across the 2011-2015 period, we identify a number of robust patterns. First, productivity growth differences tend to be larger across geographical units than across sectors. Second, structural effects tend to be weaker for employment growth than for value-added or productivity growth. Third, when the aggregation level is high (major regions or NACE+ sectors), competitive effects are dominant, but incrementing the number of geographical units (cantons) and/or the number of industrial categories (NOGA4 sectors) increases the importance and the variance of structural effects (related to incumbent, emerging or absent sectors). Fourth, year-to-year fluctuations are stronger and do not necessarily replicate the observed pattern of productivity growth sources across the whole period. Fifth, at the level of large regional and industrial categories, productivity growth has been particularly weak for the Mittelland and for the Real estate sector.

These results broadly confirm previous findings in the literature although they get in deeper details. For example, Marti et al. (2017) also find different productivity growth patterns depending on the time period studied, and a lower productivity growth for the Jura Arc which is in line with our observation for the Mittelland. The pattern of a larger heterogeneity of productivity growth across geographical units than across industrial ones is also confirmed. Estimated structural effects are weak, but the analysis is carried out at a more aggregated level than in the present paper, which is consistent with our claim that disaggregated data are needed to identify clearly structural effects.[18]

These stylized facts show that the low productivity puzzle of Switzerland hides a reality which is far more complex and varied than what aggregate performance suggests. Even if they jointly combine to generate low aggregate figures along the above-mentioned trends, productivity performances vary a lot across sectors, regions and years. This has been extensively presented and discussed in the paper.

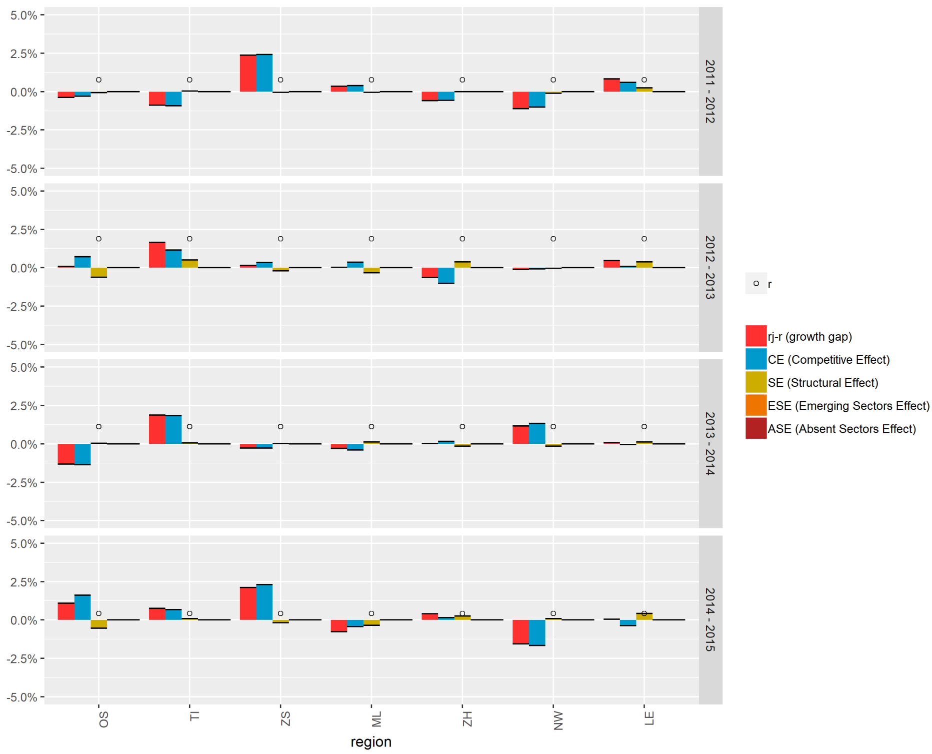
When considering an alternative sample which is biased towards larger sin-

[18] Marti et al. (2017) perform a productivity analysis on two time periods (2008-2012 and 2012-2014) for 106 MS-Regions and 19 industries using ESS data. This leads to a maximum of roughly 2000 observations per year, compared to close to 12000 for the present study (25 regions x 460 industries).

gle plant firms, the five above-mentioned stylized facts remain robust. However, detailed productivity growth rankings are altered. This calls for prudence in interpretation and constitutes a clear invitation to pursue the analysis further.

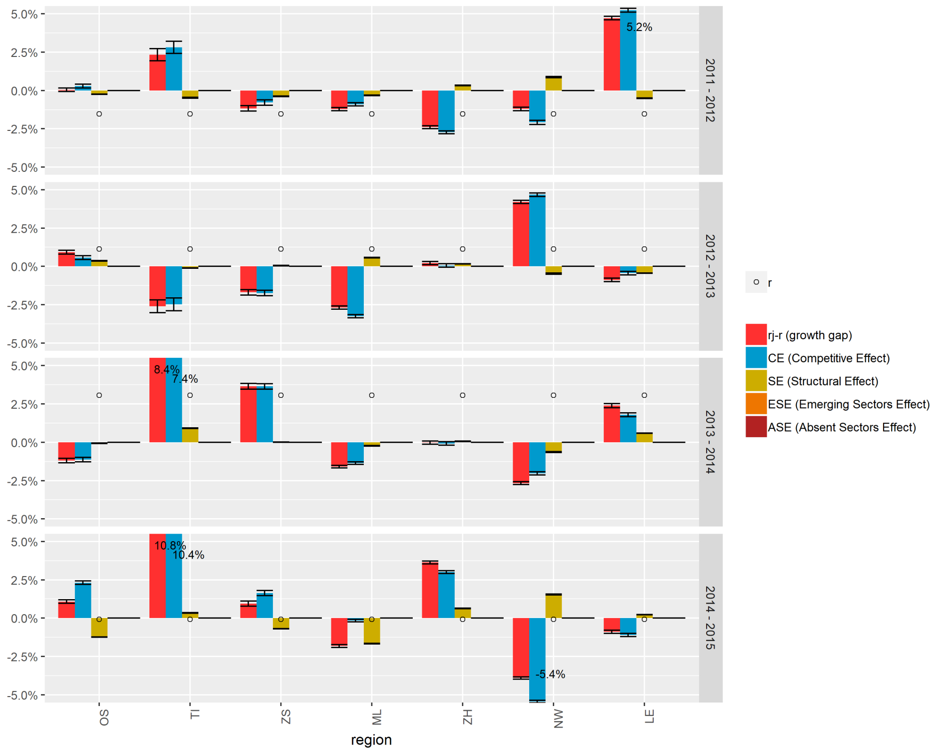
Appendix A: Detailed results for major regions 2011-2015, NACE+ sectors

Figure A.1: Detailed employment decomposition for major regions 2011-2015, NACE+ sectors.



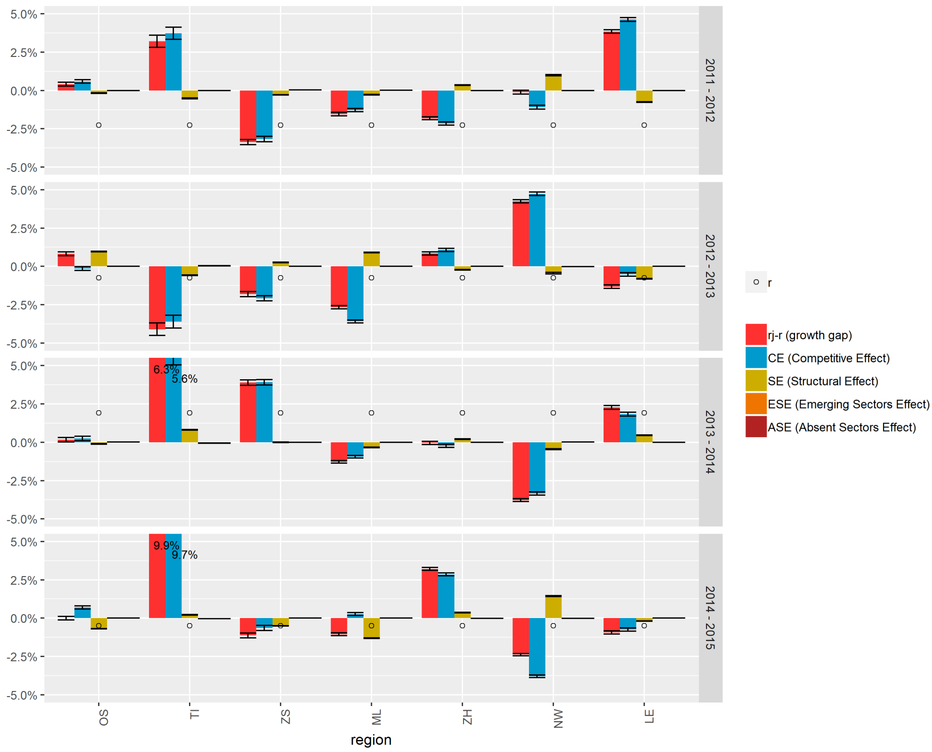
Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples.

Figure A.2: Detailed value-added decomposition for major regions 2011-2015, NACE+ sectors



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples.

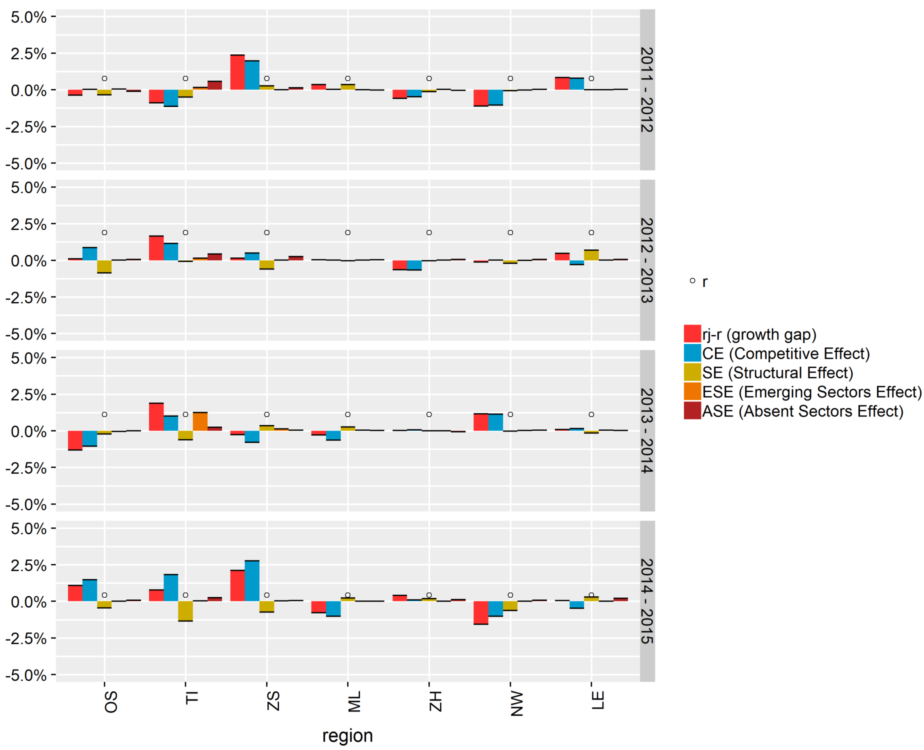
Figure A.3: Detailed productivity decomposition for major regions 2011-2015, NACE+ sectors



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples.

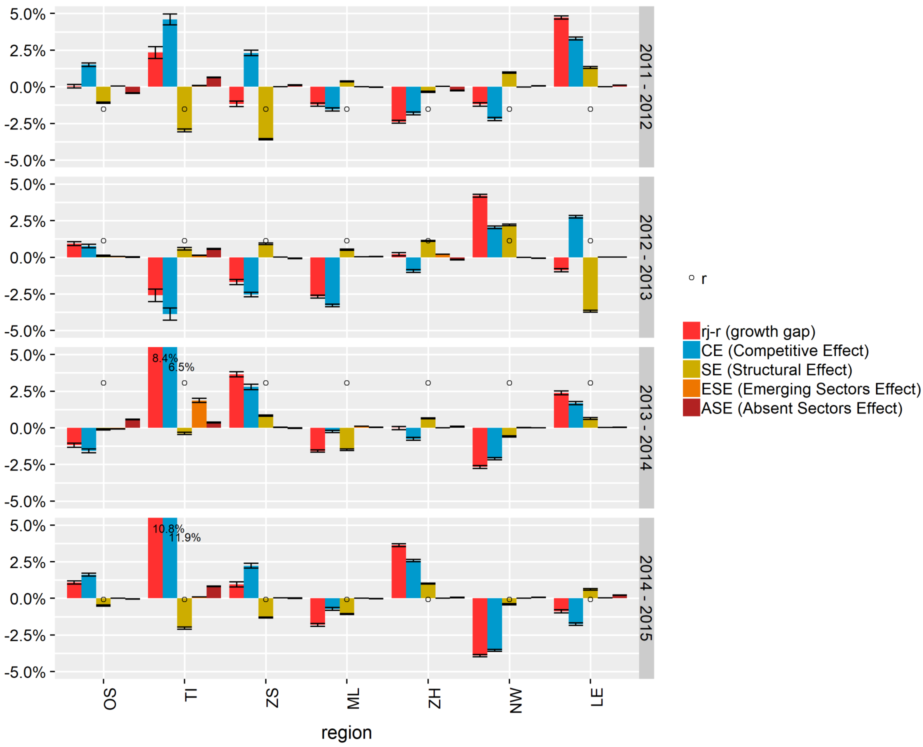
Appendix B: Detailed results for major regions 2011-2015, NOGA4 sectors

Figure B.1: Detailed employment decomposition for major regions 2011-2015, NOGA4 sectors.



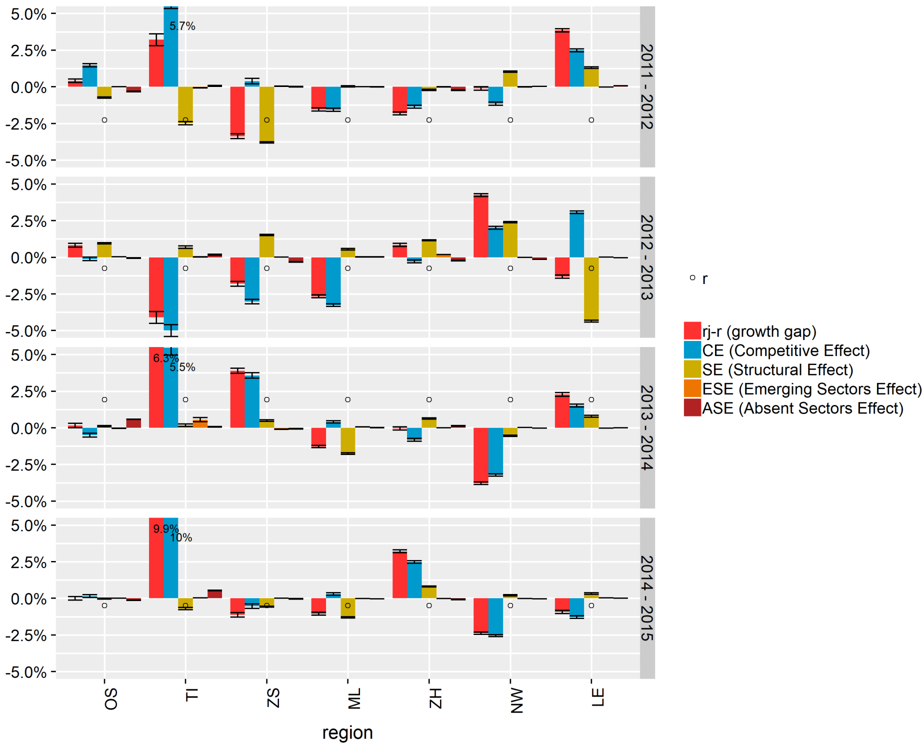
Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "°" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples.

Figure B.2: Detailed value-added decomposition for major regions 2011-2015, NOGA4 sectors.



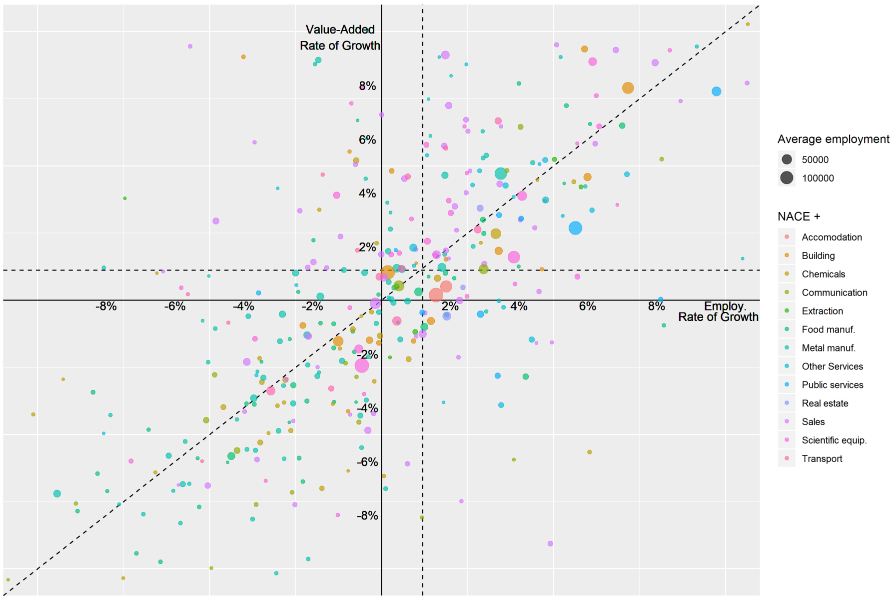
Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples.

Figure B.3: Detailed productivity decomposition for major regions 2011-2015, NOGA4 sectors.



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples.

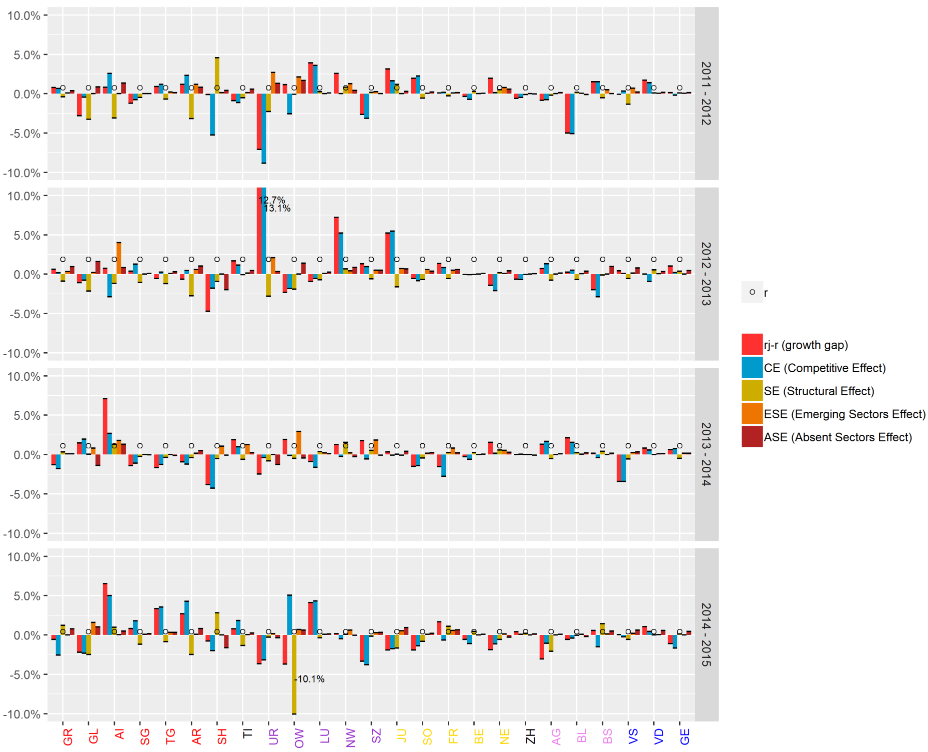
Figure B.4: Average growth of employment and value-added by NOGA4 sector 2011-2015.



Note: Annual growth over the 2011-2015 period; employment measured in full time equivalents; the size of dots is proportional to the average industrial employment; see Table 1 for names of major sectors.

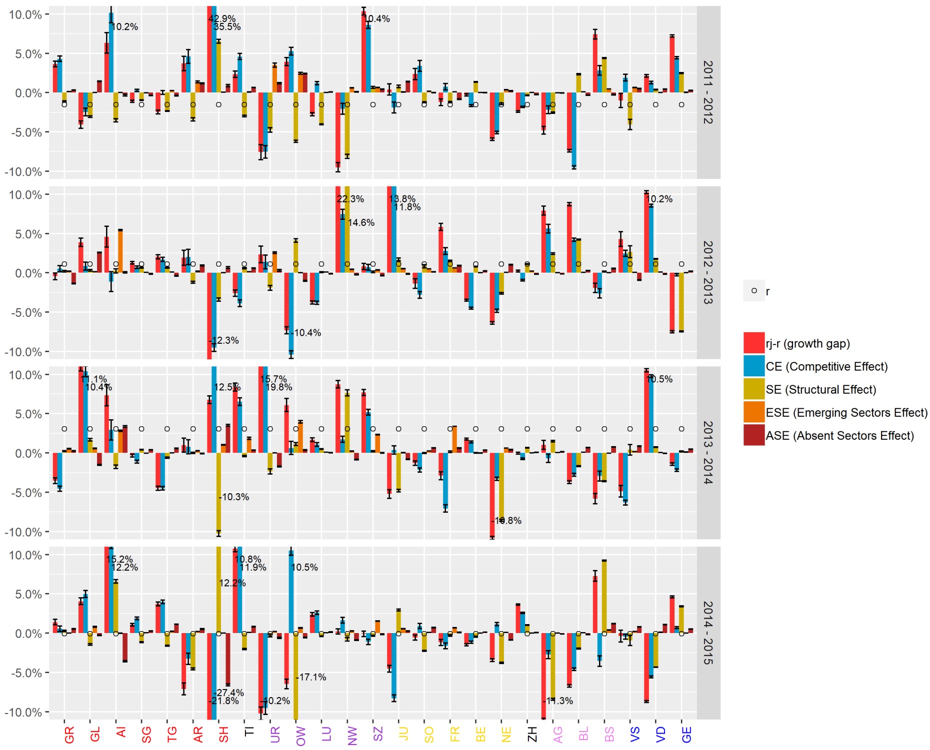
Appendix C: Detailed results for cantons 2011-2015, NOGA4 sectors

Figure C.1: Detailed employment decomposition for cantons 2011-2015, NOGA4 sectors.



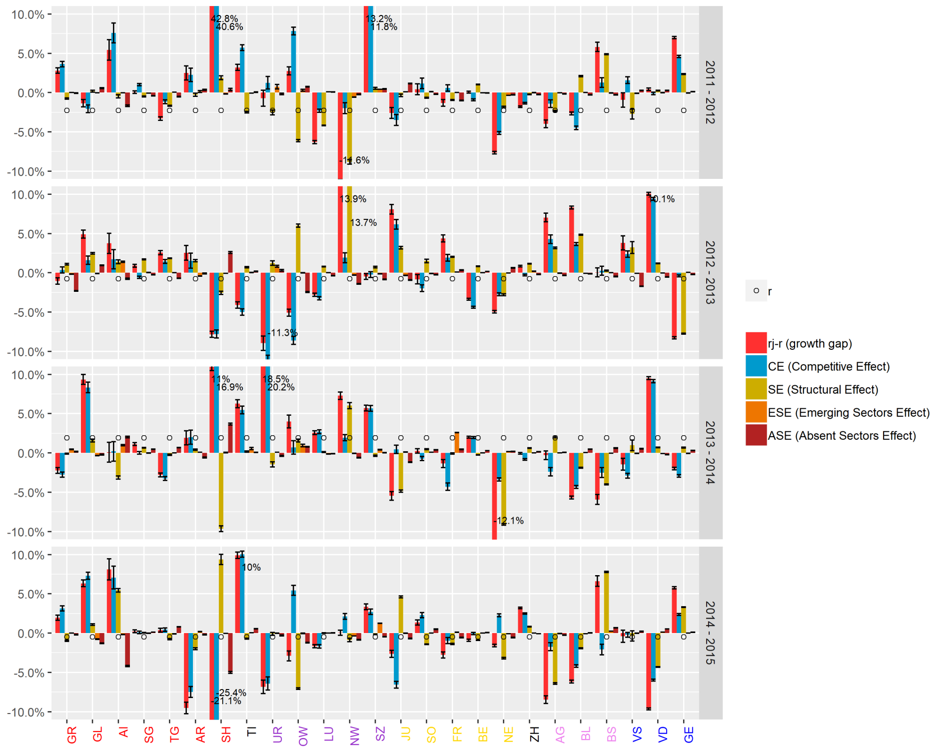
Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r). Cantons sorted in ascending average productivity order in each given major region (colored).

Figure C.2: Detailed value-added decomposition for cantons 2011-2015, NOGA4 sectors.



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r) and the top or bottom "T" the mean 95%-confidence interval from the 400 imputed samples. Cantons sorted in ascending average productivity order in each given major region (colored).

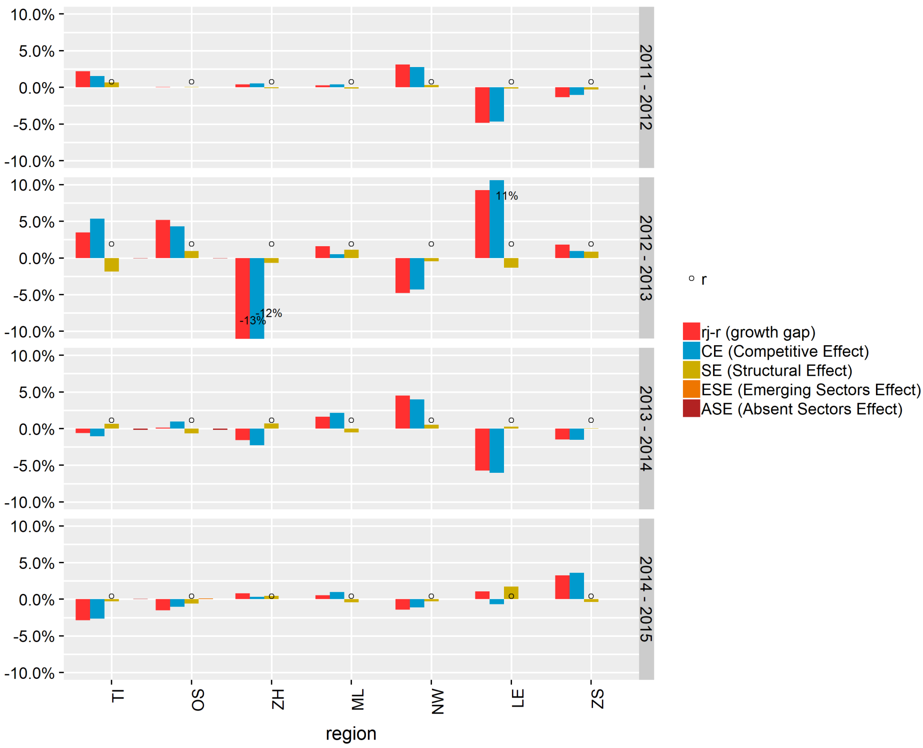
Figure C.3: Detailed productivity decomposition for cantons 2011-2015, NOGA4 sectors.



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and “NACE+” sectors. The “◦” character represents the national average (r) and the top or bottom “T” the mean 95%-confidence interval from the 400 imputed samples. Cantons sorted in ascending average productivity order in each given major region (colored).

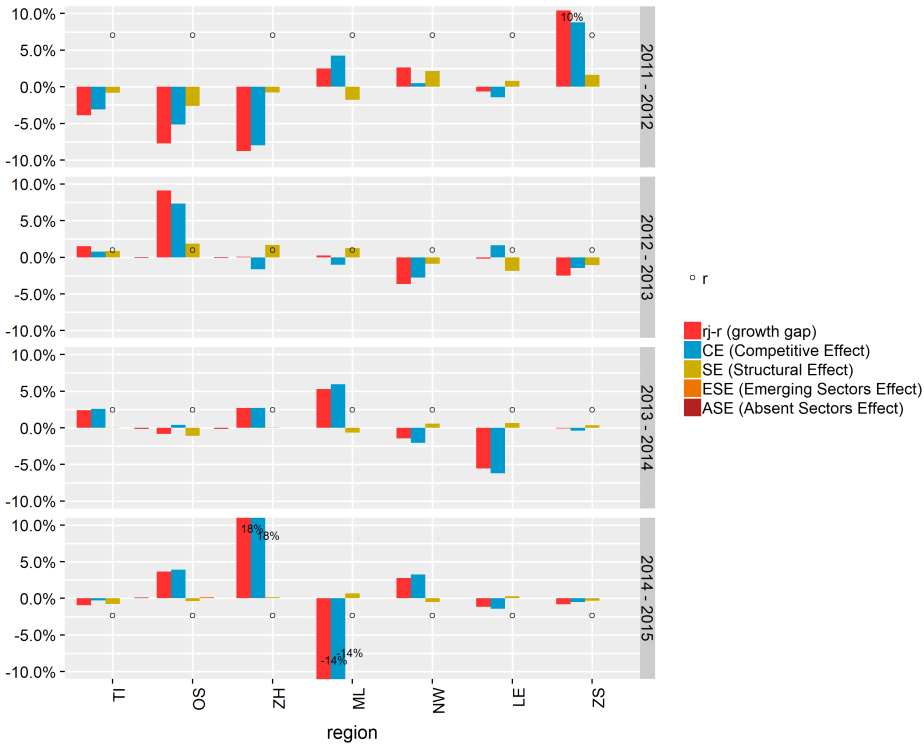
Appendix D: Detailed results for major regions 2011-2015, NACE+ sectors (restricted sample)

Figure D.1: Detailed employment decomposition for major regions 2011-2015 (restricted sample).



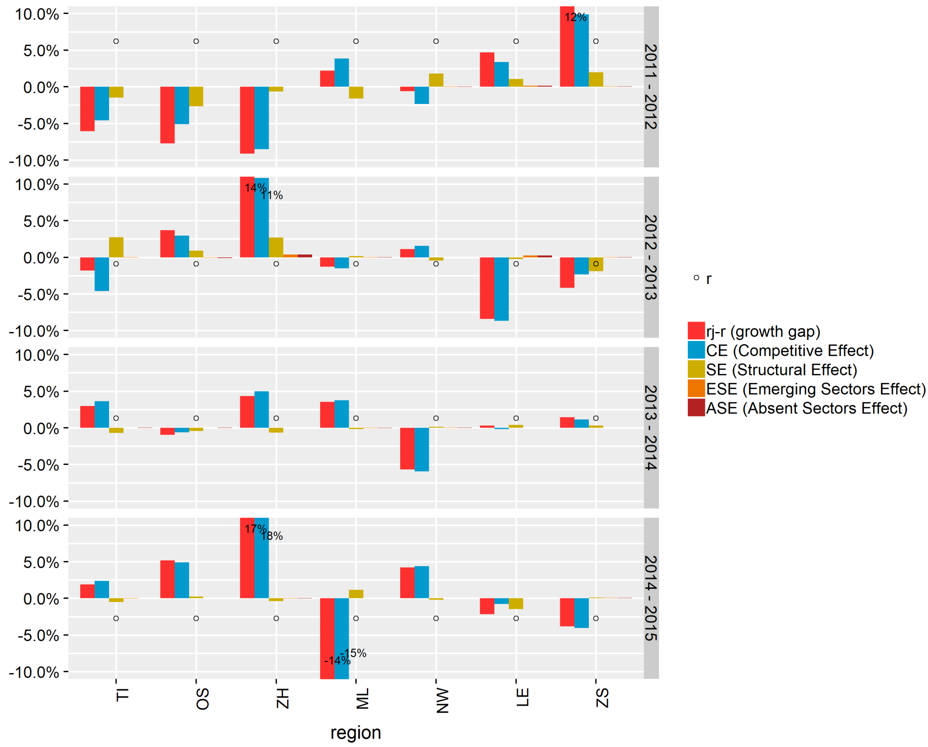
Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r).

Figure D.2: Detailed value-added decomposition for major regions 2011-2015 (restricted sample).



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r).

Figure D.3: Detailed productivity decomposition for major regions 2011-2015 (restricted sample).



Note: See equation (2), in the main text, for a definition of the different effects and Table 1 for a definition of the major regions and "NACE+" sectors. The "∘" character represents the national average (r).

Chapter 3

Measuring agglomeration economies in Switzerland

1 Introduction

Among the many approaches to estimate agglomeration economies, only a handful provide a rigorous framework to identify the actual sources of agglomeration effects. Moreover, most of the evidence is based either on the US or on EU countries (see e.g. Jofre-Monseny et al. (2014) or Holl (2004)). As a result, it is not surprising that the existing literature for Switzerland is relatively scarce. It focuses on fiscal concerns, exploiting the fiscal heterogeneity across Swiss cantons, that can be used as a natural experiment (see e.g. Brülhart et al. (2012) or Bacher and Brühlart (2013)).

This paper argues that the type, magnitude and sources of agglomeration economies in Switzerland deserve a re-examination for two major reasons. First, recent methodological developments allow for a more robust and detailed characterization of agglomeration economies and their determinants at the industry level. Second, refined estimates can be used to improve policy guidance in a variety of domains where firms localization matters, i.e. not only growth, where agglomeration effects have been suggested to be prevalent (Stohr (2014)), but also in other fields, such as industrial and labor market policies. To do so, I follow the two-step method developed by Jofre-Monseny et al. (2014), and apply it to the Swiss context. The first step decomposes agglomeration economies into localization effects and urbanization effects, the former being the productivity gains arising from spatial concentration of a specific industry, the latter being the productivity gains arising from spatial concentration of economic activity as a whole (Rosenthal and Strange (2004)). The second step identifies potential determinants of agglomeration effects, based on the Marshallian theory of agglomeration sources, i.e. labor market pooling, input sharing and knowledge spillovers (Marshall (1920)).

Using recent data is crucial to capture contemporaneous forces. To serve this purpose, I rely on the number on newborn firms and employment per industry and per municipality from the Swiss Federal Statistical Office (FSO) over the 2012-2013 period. Combined with these latest Swiss data, the Jofre-Monseny et al. (2014) method offers the additional advantage to easily deal with the endogeneity issue which affects this type of studies, without having to rely on external – and always debatable – instruments.

The next section provides a brief overview of the literature on localization of firms and agglomeration economies. Section 3 presents the empirical framework, with the methodology and data employed. Results for the first and second step of the estimation are presented in section 4, some robustness verifications are performed in section 5, while conclusion and recommendations follow in section 6.

2 Literature Overview

Since the seminal work of Marshall (1920), the empirical literature has firmly established that industries benefit from spatial concentration through productivity gains. But what hides beyond agglomeration economies? A useful preliminary step towards answering, as described by Rosenthal and Strange (2004), is to tell the difference between localization economies on the one hand, resulting from the spatial concentration of a specific industry, and urbanization economies on the other hand, resulting from the spatial concentration of economic activity as a whole. This fundamental distinction is now widely accepted in the literature.

At a deeper level of analysis, the *new economic geography* literature has been developed to formalize why economic agents tend to agglomerate leading to an unevenly distributed economic activity (see e.g. Fujita et al. (1999), Fujita and Thisse (2002) or Baldwin et al. (2005)). More recently this literature has evolved towards quantitative modelling in a similar way as the trade literature itself became more quantitatively based in the past (see e.g. Eaton and Kortum (2002)). The most recent models aim, in particular, to a better fit with the observed data (see e.g. Allen and Arkolakis (2014) or Caliendo et al. (2017)). In explaining localization choices, this literature highlights the distinction between "first nature" factors (physical endowments) and "second nature" factors (agglomeration forces through externalities). To have a more comprehensive view about these "second nature" factors, a large empirical literature has emerged.

Many empirical papers have analysed the importance of both types of agglomeration economies. Hashiguchi and Tanaka (2015) use a Bayesian approach to estimate agglomeration effects based on Chinese industry data. They find that, while localization economies do matter, urbanization economies do not seem to play any important role. Furthermore, they find evidence of gains for firms producing similar products through knowledge spillovers and input sharing. Graham (2009) uses data on British firms and a general translog production-inverse input demand system to estimate and disentangle urbanization and localization elasticities for manufacture and service industries. He finds positive localization economies in a 10 km radius from the firm with a magnitude depending on the industry. He also finds positive urbanization economies. Interestingly, retailing services, real estate, post and telecommunications and public services do not exhibit positive localization economies (i.e. they do not benefit from industry-specific concentration effects) since their localization is based on their consumers location. Therefore these service industries do not tend to concentrate.

The empirical literature on agglomeration forces faces endogeneity problems, leading to different methodologies to overcome the issue but making inter-studies comparison difficult (Combes and Gobillon (2015) or de Groot et al. (2016)). As described by Combes and Gobillon (2015), the problem may arise when a productivity increase in a given area attracts more workers (affecting the local characteristics), which in turn attracts new firms, rising productivity again. Jofre-Monseny et al. (2014) propose a very intuitive way of dealing with the endogeneity issue. By focusing on Spanish newly created firms, they tackle the simultaneity problem of firms establishments. They use a random profit *à la Carlton* for modelling the firm creation process and then estimate urbanization and localization effects by industry using a Poisson regression framework. An additional contribution of their paper is the disentanglement of the agglomeration effects into their possible sources, i.e. labor market pooling, input sharing and knowledge spillovers. Their results show that there exists a negative correlation between localization and urbanization effects, but both matter in the location decisions of the firms. Furthermore, knowledge intensity of the industry has a negative impact on localization economies but a positive impact on urbanization effects. This result is in line with the concept of “nursery cities” of Duranton and Puga (2001). They show that diversified and specialized cities can coexist since innovation takes place in large urban centers, while mature firms tend to relocate to specialized economic area where they can benefit from industry-specific effects. It is worth mentioning that most empirical studies tend to focus on manufacturing industries, although Graham (2009) campaigns for for the inclusion of services, as well as Chang et al. (2015) who, in addition, incorporate network effects.

In Switzerland, as mentioned in section 1, the existing literature on firms localization is closely linked to fiscal policies. For example, Brülhart et al. (2012) find that agglomeration economies reduce the impact of tax competition. Bacher and Brühlart (2013) find that tax progressivity is positively associated with firms births while tax level and complexity are negatively related. Other dimensions have also been explored. Axhausen et al. (2015) analyse the impact of public transport on agglomeration economies. Stohr (2014) studies agglomeration effects and the relationship between spatial concentration and economic growth in Switzerland for the period 1860-2008. This paper highlights the important role of urban policies in Switzerland. It argues that the observed densification of urban areas in the period 1860-1910 fed economic growth up to 1930. Thereafter, policies promoting less urbanization hampered economic growth, in particular during the period 1970-2000. This line of reasoning suggests that more research on agglomeration economies is needed in Switzerland, a country where growth relies substantially on the performance of small and medium enterprises and on innovative startups, whose survival rate depends on industrial localization (Renski (2011)).

In short, it is fair to say that, apart from the tax competition literature, the issue of estimating agglomeration economies in Switzerland has been quite neglected so far, in spite of both recent methodological developments and of interesting potential policy implications. The empirical exercise proposed by the present paper aims at filling this gap in the literature.

3 Empirical framework

I follow the empirical framework of Jofre-Monseny et al. (2014). As stated above their two-step procedure allows to quantify urbanization and localization economies and proposes a decomposition in their possible sources. The method makes use of data on new firms per industry and municipalities explained by non-contemporaneous employment data to avoid the simultaneity issue (new firms – employment) encountered in this type of studies. In this section, the methodology, the empirical specification and the data used are described in more details.

3.1 Methodology

First step

Following Jofre-Monseny et al. (2014), I assume that the firms creation process follows a random profit approach *à la Carlton*[1]. Abstracting form the time dimension at this stage, the profit of firm j, located in city c and belonging to industry i, noted π_{jic}, is postulated as follow:

$$\pi_{jic} = \beta^i_{loc}\, emp_{ic} + \beta^i_{urb}\, emp_{-ic} + x'_{ic}\, \gamma^i + \epsilon_{jic} \tag{1}$$

where emp_{ic} and emp_{-ic} are the log of employment levels in city c in, respectively, industry i and in all industries except industry i, along with semi-elasticity β^i_{loc} capturing localization economies and semi-elasticity β^i_{urb} capturing urbanization economies; x'_{ic} is a set of controls and γ^i the associated elasticity, while ϵ_{jic} is an unobserved firm specific error assumed to follow an extreme value type II distribution.

Carlton (1983) shows that the probability of firm j to locate in city c, $P(j \in c)$, given (1) and the distribution of ϵ_{jic}, has a conditional logit form [2]:

$$P(j \in c) = \frac{\exp(\beta^i_{loc}\, emp_{ic} + \beta^i_{urb}\, emp_{-ic} + x'_{ic}\, \gamma^i)}{\sum_c \exp(\beta^i_{loc}\, emp_{ic} + \beta^i_{urb}\, emp_{-ic} + x'_{ic}\, \gamma^i)} \tag{2}$$

where the coefficients of interest can be equivalently estimated through the following Poisson regression (Guimarães et al. (2003) [3]) with exponential mean

[1] See Carlton (1983).

[2] See McFadden (1974) for a discussion of the conditional logit model.

[3] For a discussion on this equivalence and its related literature, see Brühlart and Schmidheiny (2011, 2015).

function given by:

$$E(N_{ic}) = \exp(\beta^i_{loc}\, emp_{ic} + \beta^i_{urb}\, emp_{-ic} + x'_{ic}\, \gamma^i) \tag{3}$$

where N_{ic} denotes the number of new firms per industry i and city c. To avoid endogeneity, "chronological" simultaneity is broken between the number of new firms created (dependent variable) and employment levels (explanatory variables along with controls). This simultaneity problem arises because employment attracts new firms and new firms create employment.

For the estimation of (3), the Poisson quasi-maximum likelihood estimator (QMLE) is used (see Wooldridge, 2002, chap. 19). Applied to this problematic, the Poisson QMLE is the set of $\hat{\beta}^i_{loc}$, $\hat{\beta}^i_{urb}$ and $\hat{\gamma}^i$, belonging to the parameter space, solving :

$$\max_{\beta^i_{loc}, \beta^i_{urb}, \gamma^i} \sum_c l_c(\beta^i_{loc}, \beta^i_{urb}, \gamma^i) \quad \forall i \in I$$

where I is the set of industries and $l_c(\beta^i_{loc}, \beta^i_{urb}, \gamma^i)$ is the log-likelihood of city c (in each industry i, there are as many observations as cities c), defined as:

$$\begin{aligned} l_c(\beta^i_{loc}, \beta^i_{urb}, \gamma^i) =& N_{ic}\, (\beta^i_{loc}\, emp_{ic} + \beta^i_{urb}\, emp_{-ic} + x'_{ic}\, \gamma^i) \\ & - \exp(\beta^i_{loc}\, emp_{ic} + \beta^i_{urb}\, emp_{-ic} + x'_{ic}\, \gamma^i) \end{aligned}$$

For each industry $i \in I$, I find the parameters $(\hat{\beta}^i_{loc}, \hat{\beta}^i_{urb}, \hat{\gamma}^i)$ that maximize[4] the sum of the log-likelihood across observations (i.e. cities). As argued by Jofre-Monseny et al. (2014), if the control vector x does not include wages and rents, despite what (1) would imply (Greenstone et al. (2010)), then the elasticities found are net agglomeration effects. This means that an estimated positive elasticity for an industry should be interpreted as an increase in productivity net of cost.

Second step

The second step of this procedure is the decomposition of the estimated localization effects and urbanization effects, enclosed, respectively, in the vectors $\hat{\beta}_{loc}$ and $\hat{\beta}_{urb}$, into their possible sources. To reach this goal, localization elasticities

[4] I perform this maximization using the function mle2() from R-package bbmle. Alternative maximizations have been performed without improvement, in particular, to check for local maxima, via simulated annealing using the results of mle2() as priors.

are pooled together and regressed using ordinary least squares on indicators related to the Marshallian theory of agglomeration (see equation (4)). The same is done with the estimated urbanization elasticities (see equation (4')).

$$\hat{\beta}_{loc} = \alpha^0_{loc} + \alpha^1_{loc} \cdot lmp + \alpha^2_{loc} \cdot ks + \alpha^3_{loc} \cdot is + \alpha^4_{loc} \cdot ctr + \epsilon_{loc} \tag{4}$$

$$\hat{\beta}_{urb} = \alpha^0_{urb} + \alpha^1_{urb} \cdot lmp + \alpha^2_{urb} \cdot ks + \alpha^3_{urb} \cdot is + \alpha^4_{urb} \cdot ctr + \epsilon_{urb} \tag{4'}$$

The industry-specific indicators are labor market pooling (lmp), knowledge spillovers (ks) and input sharing (is). Equations (4) and (4') allow also for using a set of controls (ctr). Detailed specifications are described in the next subsection.

3.2 Data availability and empirical specification

In this subsection the empirical specification of each of the two steps of the methodology exposed above is presented in details, as well as the data and their limitations. For a synthetic view of these elements, please refer to Table 1.

First step

For the estimation of equation 3, data on new firms (dependent variable) and employment (independent variable) are needed. For the former, the database *Démographie des entreprises* (UDEMO) of the Federal Statistical Office (FSO) is used. This database registers all new firms (6-digits NOGA[5], employment data, legal structure, etc.) from 2001 up to 2013. For the latter, I use employment (in full-time equivalent) per city and per industry (3-digits level) from the *Statistique structurelle des entreprises* (STATENT). As its collection method is new, the 3-digits aggregation level is only available for the years 2011 to 2013, while some data exist for years 2005 and 2008 at a level of aggregation between 1- and 2-digits. As argued in subsection 3.1, simultaneity between firms' birth and employment has to be broken. This implies in the present study to restrict the sample of new firms to the years 2012 and 2013 and the sample of employment to 2011, the last year of 3-digits level data availability. For this reason, the dependent variable N_{ic} is obtained by aggregating new firms created between 2012 and 2013 by municipality and NOGA 3-digits and explanatory variables are gathered by taking the log[6] of employment levels of 2011.

[5]In Switzerland, industries are classified according to the NOGA 2008 classification.
[6]I add one to all employment levels to avoid log(0) issue.

The set of controls (vector x in (3)) includes the (log) of city area (in ha), as a large city has larger chance to be chosen by a new firm. A regional dummy is also added, as it is needed to control for regional fixed effects.[7] Due to data limitation, I am not able to control for wages or rents meaning that positive agglomeration elasticities should be interpreted as increases in productivity net of costs (Jofre-Monseny et al. (2014)).

At each step of the construction of the data, I make sure to correct for merging or dividing municipalities. Since the study is conducted at the industry level, I exclude the industries with less than 5 new firms created over the selected two years period. Therefore the final sample contains 142 3-digits industries (over 249) and 24'186 new firms (over 24'331). Table A.1 presents a short summary of firms creation per industry and Table A.2 presents new firms by municipality. These two tables point out that the largest industries and municipalities, in terms of employment, experience largest increase in new firms. The analysis of the firms-to-employment ratio reveals the most dynamic sectors and municipalities of the sample. This ratio, calculated either at industry the level (Table A.1) or municipality level (Table A.2), equals one if the share of new firms is equal to the employment share.

Second step

The second step of the procedure regresses localization and urbanization elasticities (identified in the first step) on the three Marshallian indicators as described in equations (4) and (4'). Following Jofre-Monseny et al. (2014), I construct proxies as follows:

1. Labor market pooling (lmb) is proxied by a skill specificity index for each industry. This index is given by:

$$\text{skill}_i = \frac{1}{2}\sum_o \left| \frac{L_{oi}}{L_i} - \frac{L_{o-i}}{L_{-i}} \right|$$

   where L_i is the total labor in industry i, L_{-i} is the total labor outside industry i, L_{oi} is the labor in occupation o, in industry i and L_{o-i} is the labor in occupation o outside industry i. This reflects for each industry if

[7] I add a dummy by "Swiss greater region" (i.e. Lemanic Region (Geneva, Vaud and Valais), Mittelland Region (Bern, Fribourd, Jura, Neuchâtel and Solothurn), Zurich, Easter Switzerland (Appenzell (AR, AI), Graubünden, St.-Gallen, Schaffhausen and Thurgau), Central Switzerland (Luzern, Nidwald, Obwald, Schwyz, Uri and Zug), Ticino).

it is specialised as this index measures how it diverges from the average baskets of occupations needed to operate production in the economy. This skill specifity index is constructed using data from the *Relevé structurel* (prepared by the FSO). For each industry (1- and 2-digits), it contains the (extrapolated) number of workers in Switzerland active in each of the ten occupations defined according to the *Nomenclature suisse des professions.*[8]

2. Input sharing (is) is proxied by manufactured inputs per value of sales. Additionally, I use an inputs specificity index per industry i:

$$\text{input}_i = \frac{1}{2} \sum_k \left| \frac{I_{k,i}}{I_i} - \frac{I_{k,-i}}{I_{-i}} \right|$$

where the first term is the share of inputs used by industry i from industry k and the second term is the reciprocal for the total economy. The interpretation is similar to the skill specificity index described above. It informs how the industry diverges from the average mix of inputs in its production. Data on manufactured inputs and data used to construct this index are taken from the input-output matrix prepared by the FSO. The level of aggregation is therefore between 1- and 2-digits levels. Data on industries sales come from the Swiss Finance Department, through value-added taxes (available at a 3-digits level).

3. Knowledge spillovers (ks) are captured by the share of workers having a tertiary level education (University, University of applied sciences or technical colleges) in each industry. This gives a measure of knowledge intensity of each specific industry which will be used as proxy for knowledge spillovers. The share of workers with tertiary level education by industry (2-digits) comes from the *Relevé structurel.*

Finally, I also add as control (ctr) first nature agglomeration represented by energy and primary sector inputs per value of sales. Data on energy and primary sector inputs are also derived from the input-output matrix. Including this control helps capturing the fact that firms relying on these intermediate inputs tend to locate closer to their sources for avoiding extra transport cost.

[8]In Switzerland, occupations are classified in the following categories : agricultural, forestry economy and breeding occupations; manufacturing occupations except construction works; construction and mining occupations, hotel, restaurant and personal service occupations; management, administration, banking, insurance and law-related occupations; health and teaching occupations; unknown or non-identifiable occupations.

Table 1: Summary of data availability and empirical specification.

Variable	Availability *		Use in step: †		Data source
	Period	Disaggregation level	(1)	(2)	at FSO △
New firms	2001-2013	6-digits, Municipality (696) (2396)	Dep. var.	/	Démog. des Entreprises
Employment	2005, 2008	∼2-digits, Municipality (48) (2396)	/	/	Stat. des Entreprises et Registre des Entreprises
	2011-2013	3-digits, Municipality (261) (2396)	Expl. var.	/	Stat. des Entreprises
Occupations	2010-2014	2-digits, Occupations (88) (9)	/	Labor market pooling proxy	Relevé Structurel
Value of inputs	2011	∼2-digits (48)	/	Input sharing proxy	Matrice input-output
Education	2010-2014	2-digits, Education (88) (3)	/	Knowledge spillover proxy	Relevé Structurel
Value of sales	2008-2013	6-digits (688)	/	Input sharing proxy and control	Stat. taxes sur VA
City area (ha)	2004/2009	Municipality (2396)	Control	/	Stat. de la Superficie
Energy and primary sector inputs	2011	∼2-digits (48)	/	Control	Matrice input-output

Notes:

* corresponds to the highest level of disaggregation available. Number of categories in parentheses (differences for the same disaggregation level due to data availability). *digits* corresponds to the industrial NOGA classification; ∼2-digits corresponds to an aggregation level between 1- and 2-digits; Occupations corresponds to the (extrapolated) number of workers by occupational category; Education gives the (extrapolated) number of workers holding secondary I, secondary II and terciary education level degree.

† Step (1) corresponds to the estimation of equation (3) and Step (2) corresponds to the estimation of equations (4) and (4'). Use stands for either direct or indirect use (i.e. used directly as a variable or used in the construction of a variable.)

△ Swiss Federal Statistical Office

4 Results

The next two subsections correspond to each of the two steps of the estimation procedure. The first one being the decomposition of agglomeration economies into localization effects (triggered by industry-specific employment concentration) and urbanization effects (due to overall employment concentration). The second step corresponds to exploring potential sources, based on the Marshallian theories of agglomeration, for the effects identified in the first step. Doing so helps us bringing a quantitative and comprehensive explanation of agglomeration economies.

4.1 Step 1: Decomposing agglomeration economies

The estimation is performed for the 194 industries contained in the sample. Descriptive statistics for localization and urbanization elasticities are depicted in Table 2. I find significant[9] localization elasticities for 69 industries and significant urbanization elasticities for 134 industries. Contrary to Jofre-Monseny et al. (2014), I find larger urbanization estimates, on average, than localization estimates. This points towards the important role of cities in Switzerland, in particular because of the smallness of its territory. This could be also the reflection of the flexible Swiss labor market where workers might change occupation and industries easier than in other parts of the world. Finally, this might originate form the inclusion of the service industries in the sample, because an increase in city size is particularly beneficial to them as it represents an rise in their market size.

Table 3 presents the industries with the highest and smallest localization elasticities. For instance, *Dentists and doctors activities* benefit a lot of localization economies, this is *a priori* no surprises since they need, in particular, a very skilled labor force. *Toys and games manufacturing* features a high localization elasticity, a possible explanation is that this industry need specific inputs in the production making industry spatial concentration rational. I notice that *Retail on stall and markets* benefits from significant localization and urbanization elasticities. This is expected as this industry should locate where its customers are, i.e. cities, and benefit from being surrounded by similar neighbours. It is indeed the exact structure of a market. On the side of low significant localization effects, I find construction activities. They benefit little from industry specific concentration but much more from dense urban environment (see the values of

[9] At a minimum of 5% significance level.

Table 2: Descriptive statistics of localization and urbanization elasticities.

Descriptive statistics of localization and urbanization elasticities †		
	Localization elasticity	Urbanization elasticity
Median	0.3177	0.6806
Mean	0.3766	0.7244
Standard deviation	0.1922	0.2854
Minimum	0.1006	0.2020
Maximum	1.1360	2.6270
Significant at 5%	69 industries	134 industries

Notes: † Based on the estimated elasticities with a minimum significance acceptance level of 5%.

urbanization elasticities), one can expect these industries would largely benefit from an increase in city size since they would take part in its construction. Finally, *Wholesale trade in food supplies, beverages and tobacco* exhibits also a small significant localization effect while its urbanization counterpart is pretty large. A potential explanation is that this industry would find its customers located in cities so that an increase in city size would most likely generate business.

From Table 4, we notice that *Hospital activities* is the industry featuring the highest urbanization economies. This is *a priori* a confirmation that hospitals tend to locate in dense urban area. This is no surprise that retail activities (see 2-digits industries 47 in Table 6 or e.g. *Retail of fuel in specialized stores* in Table 4) will benefit the most from an increase in city size, since this represents indirectly a rise in potential clients. A little more surprising is the particular high urbanization elasticity of *Call centers activities*. This might be the reflection of the low skilled workers needs of this industry that one can easily find in urban area. In the lower part of Table 4, the industries with the lowest significant urbanization effects such as *Management consulting* or *Fund management* are depicted. These are specialized industries, which, while still gaining from an increase in city size, benefit most from localization effects. This might the sign of the very skilled labor force that they need. *Tourist hosting and other short term hosting activities* feature the third smallest significant urbanization elasticity. A potential explanation is that this industry tend to agglomerate around tourist sites.

Looking at Tables 3 and 4, an eye-catching element appears. In industries with high urbanization economies, localization economies tend to be small. The contrary seems to hold as well. In fact, I find a correlation of -0.4663 between the two, when considering the industries for which both agglomeration effects are significant (see Appendix B for more details). This result confirms the finding of Jofre-Monseny et al. (2014). A potential explanation is proposed by these authors; based on the insights by Duranton and Puga (2001), they argue that specialized cities tend to be small, implying that, in their location decision, firms have to choose to benefit from either localization economies (coming form city specialization) or urbanization economies (coming from city size). My results are in line with the conceptual framework presented by Duranton and Puga (2001).

More generally my results are in line with Jofre-Monseny et al. (2014); I find evidence of positive agglomeration effects coming from the two forms of agglomeration economies identified by Rosenthal and Strange (2004). In contrast to Spain, analyzed by Jofre-Monseny et al. (2014), Switzerland benefits more from urbanization economies than localization economies. From this perspective, the second step of the estimation will be helpful for analyzing the underlying determinants of this finding. Furthermore, I identify a lot of heterogeneity across industries (see Appendix C).

Table 3: Localization elasticities.

Industries with the highest localization elasticities †			
NOGA 3-digits (id and name)		Localization elasticity	Urbanization elasticity
324	Toys and games manufacturing	1.1356*	0.3480
862	Dentists and doctors activities	0.8070***	0.2164
478	Retail on stalls and markets	0.8056***	0.6174***
Industries with the smallest localization elasticities †			
NOGA 3-digits (id and name)		Localization elasticity	Urbanization elasticity
412	Residential and non-residential buildings construction	0.1006*	0.7233***
463	Wholesale trade in food supplies, beverages and tobacco	0.1266*	0.7883***
439	Other activities of specialized construction	0.1403*	0.5975***

Table 4: Urbanization elasticities.

Industries with the highest urbanization elasticities †			
NOGA 3-digits (id and name)		Localization elasticity	Urbanization elasticity
861	Hospital activities	-0.1167	2.6269***
473	Retail of fuel in specialized stores	-0.2684	1.4739***
822	Call centers activities	0.2638	1.3412***
Industries with the smallest urbanization elasticities †			
NOGA 3-digits (id and name)		Localization elasticity	Urbanization elasticity
702	Management consulting	0.6775***	0.2020***
663	Fund management	0.7670***	0.2922***
552	Tourist hosting and other short term hosting activities	0.4070***	0.2951***

Notes: *p<0.05; **p<0.01; ***p<0.001
† Based on the estimated urbanization elasticities with a minimum significance acceptance level of 5%.

4.2 Step 2: Exploring agglomeration sources

I aim now to identify potential sources of the agglomeration economies estimated in the previous subsection. As argued in the section 3, I explain separately the elasticities found in step one on some potential determinants, in particular, I test for the three Marshallian theories of agglomeration, i.e. knowledge spillovers, input sharing and labor market pooling. As determinant, a variable to indicate how reliant is the industry on energy and primary inputs is added, to capture spatial concentration due to this factor. The dependent variable of each regression is, respectively, the vector of localization and urbanization elasticities significant at a minimum acceptance level of 5%. Table 5 and 6 present, respectively, results of the decomposition of localization and urbanization economies.

Table 5 indicates that education intensity (share of workers in each industry with a tertiary level diploma), used as proxy for knowledge spillovers, is an important determinant of localization elasticities. This result expresses that the more an industry relies on an highly educated workforce, the more likely it is to benefit from localization economies. This what we expect, an industry intensive in educated labor force benefits in being located in a specialized environment as innovation and information flows are facilitated by geographic proximity. Surprisingly, labor market pooling does not seem to correlate with localization elasticities. A possible explanation lies on the fact that, in Switzerland, skill specificity is correlated with education intensity (i.e. when an industry is skilled specialized, it tends to be an educated workforce intensive one). This is however not confirmed by neither my dataset nor bivariate regressions. Interestingly, we find evidence of input sharing through manufactured inputs intensity (but not trough input index). This is intuitively relevant since we expect industries relying on a large set of inputs, in particular in the manufacturing industries, to collocate in area with efficient transportation network to reduce the cost of intermediate inputs. A surprising result is the negative relationship between primary and energy inputs per value of sales and localization elasticities found (even though this is not confirmed by the bivariate regression) as I expect energy intensive industry to collocate to share infrastructures costs. Of course, these results should be handled with the appropriate caution for two reasons. First, they are base on a relative small sample (i.e. 69 observations) and second, we pool all industries together, i.e. manufacturing and service and one might believe that the determinants and agglomeration elasticities interpretation does not transfer directly from one to another. To summarize, my results point towards clear role of knowledge spillovers and input sharing in explaining localization elasticities, which is in line with the seminal work of Marshall (1920). I also find that a large fraction of localization elasticities remains unexplained, implying that one should consider, in further studies, more than the traditional Marshallian theories of agglomeration by adding other determinants such as industry openness to trade.

Table 6 presents the results of the regression of the significant urbanization elasticities on a set of potential explanatory variables. First of all, knowledge spillovers (trough education intensity) does not appear to play a role in explaining urbanization elasticities while it is the case for localization elasticities. Cities offer a more diversified environment so we do not expect industry using a high share of workers with a tertiary level diploma to benefit from an increase in municipality size. In terms of input sharing, I find evidence of negative correlation between the inputs index and the dependent variable. Industries relying on skilled workers suffer from an increase in city size. First, we expect labor

Table 5: Decomposition of Localization Economies.

	Estimated Localization Elasticities ($\hat{\beta}_{loc}$) †					
Constant	0.2435^{+} (0.1442)	0.4280*** (0.0963)	0.2909*** (0.0486)	0.3435*** (0.0269)	0.2019 (0.1251)	0.3846*** (0.0279)
Skill specificity index proxy for *labor market pooling*	0.0674 (0.2306)	-0.1280 (0.2231)				
Education intensity proxy for *knowledge spillovers*	0.3902* (0.1810)		0.2540^{+} (0.1284)			
Manufactured inputs per CHF of sales proxy for *input sharing*	0.5123^{+} (0.2684)			0.3602 (0.2637)		
Input dissimilarity index proxy for *input sharing*	-0.1020 (0.2735)				0.3390 (0.2479)	
Primary and energy inputs per CHF of sales proxy for *first nature agglo- -meration forces*	-2.2833* (0.9005)					-0.9015 (0.5984)
Observations	69	69	69	69	69	69
Adj. R^2	0.0751	-0.0086	0.0307	0.0349	0.0238	-0.0073

Notes: $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001
† Based on the estimated urbanization elasticities with a minimum significance acceptance level of 5%. Robust standard errors in ( ).

market pooling to be positively linked to localization rather than urbanization elasticities so that the negative relationship found might be the reflection of the positive effect of this determinant on localization economies. Second, it is worth mentioning that we estimate agglomeration effects net of costs, so that an increase in productivity can be countered by an increase in cost (e.g. through rents or wages). Lastly, this can be viewed through the lenses of a decrease in productivity. For example, the workforce of a city is expected to be more diversified, making it harder for a company to find the specialized workers it needs, decreasing *in fine* productivity. Finally, I also note that the proxy capturing industry usage of energy and primary inputs does not correlate with urbanization elasticities. Furthermore, I find no determinants that can explain positive urbanization elasticities. This might be due to the inclusion of service industries in my sample. From this perspective, an increase in city size is intrinsically linked to a rise in market size which is not captured by this regression framework.

Finally, for robustness purposes, I redo the same exercise but I restrict my

Table 6: Decomposition of Urbanization Economies.

	Estimated Urbanization Elasticities ($\hat{\beta}_{urb}$) †					
Constant	1.1102*** (0.1305)	0.9038*** (0.0957)	0.6763*** (0.0500)	0.7196*** (0.0287)	0.8640*** (0.1550)	0.7188*** (0.0259)
Skill specificity index proxy for *labor market pooling*	-0.5055* (0.2457)	-0.4746^{+} (0.2722)				
Education intensity proxy for *knowledge spillovers*	0.2525 (0.2649)		0.1575 (0.1712)			
Manufactured inputs per CHF of sales proxy for *input sharing*	0.2556 (0.2490)			0.0474 (0.1916)		
Input dissimilarity index proxy for *input sharing*	-0.5950 (0.3852)				-0.2730 (0.2804)	
Primary and energy inputs per CHF of sales proxy for *first nature agglo- -meration forces*	0.4214 (0.5226)					0.3797 (0.4663)
Observations	134	134	134	134	134	134
Adj. R^2	0.0370	0.0286	-0.0011	-0.0072	0.0018	-0.0057

Notes: $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001
† Based on the estimated urbanization elasticities with a minimum significance acceptance level of 5%. Robust standard errors in ( ).

Table 7: Decomposition of Urbanization and Localization Economies.

	$\hat{\beta}_{urb}$ †	$\hat{\beta}_{loc}$ †
Constant	0.7463***	0.2200
	(0.0939)	(0.1400)
Skill specificity index	-0.3473*	0.1692
proxy for *labor market pooling*	(0.1470)	(0.1634)
Education intensity	0.0102	0.3884**
proxy for *knowledge spillovers*	(0.1490)	(0.1380)
Manufactured inputs		
per CHF of sales	-0.2478	0.1422
proxy for *input sharing*	(0.1639)	(0.2821)
Input dissimilarity index	-0.0345	-0.1111
proxy for *input sharing*	(0.1975)	(0.2200)
Primary and energy inputs		
per CHF of sales	0.2924	-2.0421*
proxy for *first nature agglo-*	(0.7949)	(0.9204)
-meration forces		
Observations	66	66
Adj. R^2	0.0543	0.0403

Notes: *p<0.05; **p<0.01; ***p<0.001
† Based on the estimated urbanization or localization elasticities with a minimum significance acceptance level of 5%.
Robust standard errors in ( ).

sample to industries whose estimated urbanization and localization are both significant. Overall three determinants of agglomeration economies stay significant, skill specificity index for urbanization elasticities and education intensity and primary and energy inputs per value of sales for localization elasticities. This points towards the crucial role for labor force in explaining agglomeration economies, while the result concerning the first nature agglomeration forces proxy is more surprising. The relative importance of the labor force determinants is, of course, closely due to the fact that I include service industries in the analysis, that typically depend very little on physical inputs and much more on its workers. These results will be confronted to alternative specification to test for their robustness in section 5. At this stage, it is fair to say that public policies should, in particular, promote labor mobility to allow for a pertinent allocation of workers across industries.

5 Robustness

In this section, I explore different specifications to test for the general validity of the results presented so far. This includes, in particular, the use of Swiss labor market regions instead of political municipalities as units of observation. A time consistency check of the estimates is also done using data over the years 2005-2007, 2008-2010 and 2011-2013.[10]

5.1 Alternative definition of cities

As described in section 3, I made use of Swiss political municipalities as observation units. One could argue that this is problematic because a political municipality is not necessarily relevant in economic terms. In this subsection, I perform the same analysis but using Swiss labor market regions[11] instead of municipalities. Descriptive statistics of estimated agglomeration economies under this alternative setting are presented in Table 8.

This robustness exercise slightly increases the number of industries featuring a significant localization effects, while it greatly reduces the number of significant urbanization effects. Detailed results are varied and reported in Appendix D. For instance, high localization economies remain significant for *Dentist and doctors activities*, but disappear for *Toys and games manufacturing*. Among the

[10] I thank M. Brühlart for suggesting this extension.

[11] Switzerland is divided in 16 such regions as defined by the FSO.

Table 8: Descriptive statistics of localization and urbanization elasticities considering Swiss labor market regions instead of political municipalities.

Descriptive statistics of localization and urbanization elasticities †		
	Localization elasticity	Urbanization elasticity
Median	0.9027	0.6506
Mean	0.9863	0.5178
Standard deviation	0.5671	0.9787
Minimum	-1.2634	-1.9019
Maximum	3.1329	2.4195
Significant at 5%	75 industries	41 industries

Notes: † Based on the estimated elasticities with a minimum significance acceptance level of 5%.

three industries featuring the highest urbanization elasticities, only *Call centers activities* remains significant.

As reported by Table 8, using labor market regions instead of municipalities drastically increases localization elasticities (average and median), while urbanization elasticities remain close to the original ones. In both cases, the volatility of the estimates rises. Average localization elasticities become larger than urbanization ones, contrary to my initial results but in line with Jofre-Monseny et al. (2014).

An important result of section 4.1 is the negative relationship between both type of agglomeration economies. This relationship appears to be even stronger when using labor market regions instead of municipalities. The correlation between (5% significant) localization and urbanization estimates is -0.9266, almost double the original figure. This strongly confirms both my initial findings and Jofre-Monseny et al. (2014) results.[12]

As additional robustness check, I explain separately the estimated agglomeration economies on their potential determinants (see section 4.2) capturing,

[12] The restriction of keeping agglomeration economies significant at 5% left us with only 22 observations, meaning this result should be considered with care (see Appendix D).

in particular, the three Marshallian theories of agglomeration. Localization effects appears to be driven by labor market pooling, trough the skill specificity index variable. This could be expected as industries with a particular labor demand benefit from sharing a common labor market. Surprisingly, the input index seems to decrease the localization economies. Concerning the other type of agglomeration effect, the only significant determinant is labor market pooling that depresses urbanization elasticities. The inverse impact of the skill specificity index on both type of agglomeration effects helps understanding the negative relationship between them.

To conclude, using labor market regions instead of municipalities, validates the importance of both types of agglomeration economies. Contrarily to the previous results, but according to (Jofre-Monseny et al., 2014), localization elasticities are found larger, on average, than urbanization ones. The evidence is more mixed when looking at individual industrial results, but, crucially, it confirms the negative relationship between localization and urbanization economies, which seems to be the outcome of the labor market pooling agglomeration effects.

5.2 Introducing the time dimension

In this subsection, I try to exploit the time structure of the data. Unfortunately, the panel dimension is limited, with employment data for the years 2011 and 2012 and the number of new firms created, respectively, over the years 2012 and 2013. This is not enough to run a panel regression, but I can pool all observations, insert a time dummy and estimate the agglomeration effects. As I do not aggregate the number of new firms over two years, I conduct the estimation based on labor market regions rather than municipalities to have enough non-zero observations.

As apparent from Table 9, the inclusion of a time dummy does not change much the results presented in subsection 5.1. Four more localization effects are now significant[13], while there is one less on the urbanization effects side.[14]

Performing the second step of the estimation with the new agglomeration estimates produces the results presented in Appendix E. The localization elas-

[13]This concerns industries 259, 563, 582 and 750.

[14]Three urbanization effects loose their significance (701, 711 and 799) and two effects become significant (477 and 721).

Table 9: Descriptive statistics of localization and urbanization elasticities including a year dummy.

Descriptive statistics of localization and urbanization elasticities †		
	Localization elasticity	Urbanization elasticity
Median	0.9092	0.6027
Mean	1.0233	0.4766
Standard deviation	0.5610	1.0227
Minimum	-1.2205	-1.9452
Maximum	3.1345	2.3857
Significant at 5%	79 industries	40 industries
	9 time dummies † †	3 time dummies † †

Notes: † Based on the estimated elasticities with a minimum significance acceptance level of 5%.
† † In total, 14 time dummies are significant at 5%.

ticities seem to be driven by labor market pooling. This is in line with my original findings that this type of agglomeration economy is induced by labor force components; education intensity when using municipalities as units of observation and the skill specificity index when considering labor market regions (with or without a time dummy).

The surprising outcome that input sharing has a negative impact on localization economies (see subsection 5.1) is here refuted. The negative relationship appears when explaining the estimates only with this determinant, but it does not resist the inclusion of other regressors. Regarding urbanization economies, the negative relationship between these effects and labor market pooling is confirmed. Furthermore, it appears that knowledge spillovers are negatively correlated with urbanization economies. One potential explanation is that education intensive industries tend to be more specialized and less attracted by the more diversified environment of larger regions. Caution is required here, as the sample for the estimation of the determinants of urbanization economies is small (only 40 industries left).

In short, exploiting the time dimension by estimating agglomeration economies using labor market regions and adding a time dummy does not seriously alter the results of subsection 5.1 as only a few time dummies remain significant in the exercise. The –surprisingly– negative relationship between localization elasticities and the input sharing proxy is not robust. This confirms the important role of labor force factors identified in section 4.

5.3 Time consistency of the estimates

The results presented in section 4 are constructed on employment data for year 2011 and data on new firms aggregated over the years 2012 and 2013. As described in Table 1, this is due to the limited availability of employment data as the collection method changed in 2011. Older data corrected for methodological differences in the collection method do exist but at a higher level of aggregation (NOGA 1,2-digits rather than 3-digits) and only for two years (2005, 2008). Making use of this information might be helpful in understanding the general validity of the previous results from the time consistency perspective. The purpose of this subsection is therefore to answer to the following question: how much do the estimates rely on the selection year? To investigate that point, I estimate agglomeration effects based on three different samples:

1. Employment data of 2005 and new firms created over the years 2006-2007. As described above, the employment data are only available at a level of aggregation between NOGA 1- and 2-digits, so that I have a restricted sample of 48 industries.

2. Employment data of 2008 and new firms created over the years 2009-2010, with a similar sample of 48 industries.

3. Employment data of 2011 and new firms created over the years 2012-2013. These are the original data I used for the initial estimation. For comparison purposes, I aggregate the NOGA 3-digits industries to the hybrid NOGA 1,2-digits.

The detailed results of this exercise are presented in Appendix F, while descriptive statistics can be found in Table 10. Localization elasticities appear to be stable over the studied period, although the estimates for year 2011 seem more volatile. The median of the localization effects for year 2011 is close to the average of the initial effects reported in Table 2. Regarding urbanization economies, the median for year 2011 is relatively low compared to the other years and to the initial estimates, but the standard deviation is also smaller.

In sum, even though there are small differences and the industrial classification level is higher, the estimates of agglomeration economies appear to be rather stable over time, in particular for localization effects. This validates the selection method used for the initial estimates, i.e. retaining 2011 employment data and new firms over the years 2012 and 2013.

5.4 Other robustness tests

In the estimation of the agglomeration economies, the default log-likelihood optimization method in the R-package *bblme* is *optim*. To check whether the parameters maximizing the log-likelihood were not local maxima, I used simulated annealing using the results of the first optimization as priors. This returned the same results pointing towards numerical robustness of the optimization method.

Regarding the second step, I also added a control variable capturing openness to trade of each industry based on exports and imports data of the input-output matrix.[15] Results are presented in Table 11. The regression of the initial agglomeration estimates (based on municipalities) adding openness to trade to the list of potential determinants, confirms the previous results presented in subsection 4.2. The estimates obtained using labor market regions as observation units seem to be more sensible to this determinant. Indeed, openness to trade

Table 10: Descriptive statistics of localization and urbanization elasticities considering alternative time periods and higher level of aggregation.

Descriptive statistics of localization and urbanization elasticities †						
	Localization Elasticities ($\hat{\beta}_{loc}$)			Urbanization Elasticities ($\hat{\beta}_{urb}$)		
	2005 † †	2008	2011	2005	2008	2011
Median	0.3341	0.3148	0.3231	0.6461	0.6896	0.5688
Mean	0.3492	0.3422	0.3064	0.6663	0.6908	0.6269
Standard deviation	0.1378	0.1321	0.2479	0.2390	0.2507	0.2070
Minimum	0.1107	0.1012	-0.8407	0.2416	0.1958	0.2595
Maximum	0.7574	0.6721	0.6096	1.7521	1.4774	1.1491
Significant at 5%	31 industries	29 industries	31 industries	43 industries	45 industries	43 industries

Notes: † Based on the estimated elasticities with a minimum significance acceptance level of 5%.
† † Each year refers to the employment data used. For example, for the estimation of $\hat{\beta}_{loc}$ of 2005, I used empl. data of 2005 and keep new firms created over the years 2006,2007 (see section 5.3).

[15] Only available at NOGA 1,2-digits.

has a negative impact on localization elasticities and a positive on urbanization ones. This might be due to the fact that a larger region is likely to be more connected. It also constitutes an additional factor that could explain the negative relationship between the two types of agglomeration economies, at least at the labor market regions level.

Table 11: Openness to trade as a potential determinant.

Aggregation	Municipalities		labor market regions		labor market regions	
Year dummy	No		No		Yes	
	$\hat{\beta}_{loc}$ †	$\hat{\beta}_{urb}$ †	$\hat{\beta}_{loc}$ †	$\hat{\beta}_{urb}$ †	$\hat{\beta}_{loc}$ †	$\hat{\beta}_{urb}$ †
Constant	0.2631	1.0933***	1.3314**	1.6740	1.4127**	1.8255
	(0.1525)	(0.1332)	(0.4252)	(1.1680)	(0.4426)	(1.0780)
Skill specificity index	0.06087	-0.4935*	0.7718	-3.2315*	0.6739	-4.1473*
proxy for *labor market pooling*	(0.2329)	(0.2364)	(0.5938)	(1.3648)	(0.5973)	(1.8305)
Education intensity	0.3634$^+$	0.2622	0.3490	-2.9059	0.1747	-3.2165
proxy for *knowledge spillovers*	(0.1864)	(0.2587)	(0.5416)	(1.8419)	(0.5413)	(2.0345)
Manufactured inputs per CHF of sales	0.4230	0.2681	0.9372	-3.0441	0.8855	-2.2394
proxy for *input sharing*	(0.2772)	(0.3220)	(0.7870)	(2.6068)	(0.8921)	(2.4861)
Input dissimilarity index	-0.1377	-0.5661	-1.4819$^+$	1.7479	-1.4229	1.9943
proxy for *input sharing*	(0.2931)	(0.3752)	(0.8605)	(2.8438)	(0.8660)	(2.6873)
Primary and energy inputs per CHF of sales	-1.9516$^+$	0.3734	-3.5550	2.8259	-2.8141	3.7531
proxy for *first nature agglo- -meration forces*	(1.1028)	(0.5152)	(2.9631)	(3.7167)	(3.4668)	(3.7686)
Trade openness	0.0206	-0.0053	-0.1850**	0.3094*	-0.1345$^+$	0.2577$^+$
	(0.0359)	(0.0255)	(0.0634)	(0.1357)	(0.0778)	(0.1463)
Observations	69	134	75	41	79	40
Adj. R^2	0.0694	0.0246	0.0655	0.2036	0.0479	0.2395

Notes: $^+$p<0.1; *p<0.05; **p<0.01; ***p<0.001
† Based on the estimated urbanization elasticities with a minimum significance acceptance level of 5%. Robust standard errors in ( ).

6 Conclusion

The two-step procedure proposed by Jofre-Monseny et al. (2014) allows me to quantify and disentangle agglomeration economies in Switzerland using recent data on newly created firms. I find evidence of both localization and urbanization economies, the latter being more important in terms of magnitude, contrarily to the Spanish case. This highlights the crucial role of dense cities in Switzerland, and may also be linked to the inclusion of services sectors in the sample. This result, however, is not robust to the usage of labor market regions as units of observation. Besides, my results confirm that localization and urbanization are negatively related, i.e. sectors with high localization economies tend to exhibit low urbanization economies, and vice versa. This sustains further empirical scrutiny in the second step of the estimation, which analyses the determinants of both types of agglomeration economies.

As it turns out, two explanatory factors seem to be at the heart of this inverse relationship. On the one hand, the extent of input sharing appears to boost localization effects while depressing urbanization effects. On the other hand, skill-based indicators have opposite effects on the two types of elasticities: localization elasticities are positively associated with the tertiary education indicator, and urbanization elasticities negatively associated with the skill-specificity indicator. This suggests that industries characterized by a high degree of specificity, whether in terms of specialized inputs or particular skills of the labor force, exhibit strong localization effects and tend to cluster in similar areas, irrespectively of the size of the agglomerations. Oppositely, broad-based industries, which are flourishing in large urban centers, suffer from being located in highly specialized regions. This result is robust across specifications and is not only in line with the seminal work of Marshall (1920) regarding input sharing and knowledge spillover effects, but also with the more recent model of "nursery cities" of Duranton and Puga (2001), which suggests that large urban centers are favorable to innovative firms, while more mature industries tend to cluster in specific areas.

However, prudence in interpretation is required given that the part of the agglomeration effects explained by second-step regressions remain relatively low. Moreover, although intuitive and robust, our results are still vague regarding the mechanisms which are at work on the labor or the input markets. This makes it difficult to articulate proper policy recommendations at this stage. Further research efforts should aim at easing these empirical bottlenecks.

Appendix A: Descriptive statistics

Table A.1: New firms per industry.

NOGA 3-digits (id and name)		New Firms	Employment (% of total)	New firms to empl. (% of new firms / % of employm.)
Top 5% industries with the most firms creations				
702	Management consulting	2348	1.29	7.50
620	Programming, informatics consulting and other informatics activity	1437	2.46	2.41
711	Engineering and architecture activities	1422	3.12	1.88
433	Building completion work	1019	2.00	2.11
432	Electric installation, plumbing and other installation work	811	3.22	1.04
464	Wholesale trade of domestic goods	733	2.02	1.50
683	Property operations on behalf of third parties	666	1.05	2.62
Industries with median firms creations				
NOGA 3-digits (id and name)		New Firms	Employment (% of total)	New firms to empl. (% of new firms / % of employm.)
381	Waste collection	10	0.12	0.36
422	Wire-line and networks construction	10	0.11	0.36
429	Other civil engineering work	10	0.07	0.59
611	Wire-line telecommunication	10	0.65	0.06
803	Investigation activities	10	0.004	10.5
853	Secondary school teaching	10	2.00	0.02
Top 5% industries with the least firms creations				
NOGA 3-digits (id and name)		New Firms	Employment (% of total)	New firms to empl. (% of new firms / % of employm.)
231	Glass manufacturing	5	0.15	0.14
257	Cutlery, tooling and hardware manufacturing	5	0.41	0.05
259	Manufacturing of other type of metal based products	5	0.30	0.07
324	Toys and games manufacturing	5	0.01	1.92
582	Software edition	5	0.01	1.60
639	Other information service	5	0.05	0.39
370	Treatment and collection of waste water	6	0.13	0.19

Notes: Industries with less than 5 new firms are excluded from the sample.
The sample features 142 3-digits industries (over 249) and 24'186 new firms created (over 24'331). Employment is measured in full-time equivalents.
Total denotes the total of full-time equivalents of the sample.

Table A.2: New firms per municipality.

Municipality (id and name)		New Firms	Employment (% of total)	New firms to empl. (% of new firms / % of employm.)
Top 6 municipalities with the most firms creations				
261	Zürich	1782	8.48	0.87
6621	Genève	1178	3.66	1.33
5192	Lugano	971	1.12	3.58
2701	Basel	540	3.90	0.57
1711	Zug	528	0.93	2.36
5586	Lausanne	455	2.38	0.79
6 selected† municipalities with median firms creations				
3784	Pontresina	2	0.0529	0.16
5489	Mex (VD)	2	0.0448	0.18
2208	Matran	2	0.0326	0.25
5429	Longirod	2	0.0005	15.53
3808	Rossa	2	0.0004	18.89
5476	Chevilly	2	0.0004	20.05
6 selected† municipalities with no firms creations				
444	Sonceboz-Sombeval	0	0.0306	0
5744	Ballaigues	0	0.0285	0
3982	Disentis/Mustér	0	0.0245	0
3613	Pignui	0	0.0000119	0
5109	Gresso	0	0.0000108	0
2033	Morens (FR)	0	0.0000100	0

Notes: † 282 municipalities features two new firms and 525 municipalities features no firms creation. In both cases, the three municipalities with most and least employment are presented.
Municipalities are in state of December 2013.

Appendix B: Negative relationship between $\hat{\beta}_{loc}$ & $\hat{\beta}_{urb}$

To assess if there exists a significant negative relationship between the localization and urbanization effects, we run the following OLS regression:

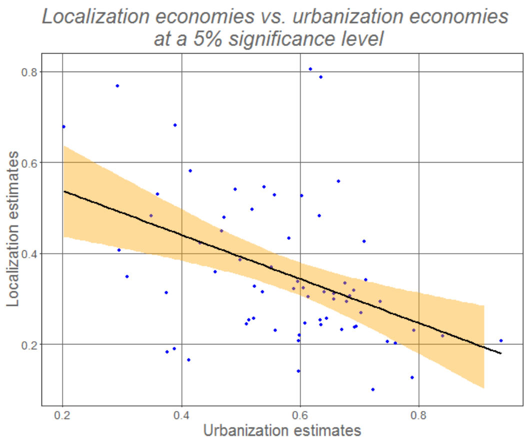
$$\hat{\beta}_{loc} = \alpha_0 + \alpha_1 \cdot \hat{\beta}_{urb} + \epsilon$$

keeping only industries with both agglomeration elasticities significant at a minimum acceptance level of 5%. The results of this regression are presented in the following table and figure.

Table B.1: Negative relationship between $\hat{\beta}_{loc}$ & $\hat{\beta}_{urb}$

	$\hat{\beta}_{loc}$
Constant	0.6351***
	(0.0798)
$\hat{\beta}_{urb}$	-0.4859***
	(0.1237)
Observations	66
Adj. R^2	0.1759

Notes: *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in ( ).



We find a 1%-significant negative slope coefficient ($\hat{\alpha}_1$) that clearly indicates a negative relationship between localization elasticities ($\hat{\beta}_{loc}$) and urbanization elasticities ($\hat{\beta}_{urb}$).

Appendix C: Localization and urbanization estimates

Table C.1: Localization and urbanization estimates

Estimates of localization and urbanization elasticities for the 142 3-digits industries			Estimates of localization and urbanization elasticities for the 142 3-digits industries		
NOGA 3-digits	Localization elasticity	Urbanization elasticity	NOGA 3-digits	Localization elasticity	Urbanization elasticity
105	0.13	0.73***	310	0.10	0.90***
107	-0.06	1.05***	321	0.48***	0.35***
108	0.02	0.71***	324	1.14*	0.35
110	0.32	0.38*	325	0.17	0.91***
139	-0.02	0.62***	329	-0.02	0.78***
141	0.15	0.78***	331	0.19*	0.39***
151	-0.25	0.98***	332	-0.46	0.71***
162	0.07	0.52***	351	0.04	0.74***
181	0.26	0.75***	370	-0.32	1.16***
204	0.15	0.90***	381	0.04	0.72***
212	0.00	1.16***	383	-0.26	0.95***
222	0.21	0.27	411	0.23*	0.67***
231	-0.81	0.72*	412	0.10*	0.72***
237	0.21	0.63***	421	-0.30	0.94***
251	0.21	0.48***	422	0.04	0.57*
256	0.17*	0.41***	429	0.02	0.34
257	0.51	1.23***	431	0.31***	0.38***
259	0.40	0.41	432	0.24***	0.51***
261	-0.42	1.00***	433	0.37***	0.55***
265	0.42***	0.43***	439	0.14*	0.60***
279	0.30	0.66***	451	0.11	0.67***
282	0.03	0.52***	452	0.35***	0.31***
289	0.09	0.71***	453	0.19	0.59***
293	0.56*	0.43	454	0.01	0.62***
301	0.79*	0.63***	461	0.43***	0.58***

Notes: *p<0.05; **p<0.01; ***p<0.001

Estimates of localization and urbanization elasticities for the 142 3-digits industries		
NOGA 3-digits	Localization elasticity	Urbanization elasticity
462	0.21	0.86***
463	0.13*	0.79***
464	0.30***	0.66***
465	0.29***	0.68***
466	0.26***	0.64***
467	0.21***	0.75***
469	0.24***	0.69***
471	0.09	0.82***
472	0.30*	0.61***
473	-0.27	1.47***
474	0.14	0.69***
475	0.12	0.66***
476	0.25*	0.51***
477	0.34***	0.60***
478	0.81***	0.62***
479	0.24***	0.64***
493	0.29***	0.74***
494	0.22***	0.60***
511	0.52	1.17***
521	-0.17	0.93***
522	0.09	0.97***
532	0.32***	0.61***
551	0.10	0.58*
552	0.41***	0.30***
561	0.15	0.76***
562	0.33***	0.52***
563	0.53*	0.56*

Estimates of localization and urbanization elasticities for the 142 3-digits industries		
NOGA 3-digits	Localization elasticity	Urbanization elasticity
581	0.24*	0.69***
582	-10.39	0.97***
591	0.34***	0.71***
592	0.43***	0.71***
611	-0.09	0.93*
619	0.20	0.94***
620	0.32***	0.59***
631	0.21***	0.94***
639	0.15	1.30*
642	0.56***	0.66***
649	0.55***	0.54***
661	0.48***	0.63***
662	0.20***	0.76***
663	0.77***	0.29***
681	0.48***	0.47***
682	0.19	0.64***
683	0.36***	0.46***
691	0.53***	0.60***
692	0.53***	0.36***
701	0.11	1.09***
702	0.68***	0.20***
711	0.31***	0.54***
712	0.10	0.77***
721	0.22***	0.84***
722	0.54*	0.49*
731	0.31***	0.64***
732	0.17	0.96***

Notes: *p<0.05; **p<0.01; ***p<0.001

Estimates of localization and urbanization elasticities for the 142 3-digits industries		
NOGA 3-digits	Localization elasticity	Urbanization elasticity
741	0.50***	0.52***
742	0.32***	0.69***
743	0.68***	0.39***
749	0.31***	0.66***
750	-0.09	0.49***
771	0.05	0.72***
772	0.10	0.66***
773	0.23	0.84***
774	0.20	1.21***
781	0.31***	0.68***
782	0.09	1.03***
791	0.27***	0.70***
799	0.33*	0.68***
801	0.10	0.68***
802	-0.33	0.84***
803	0.37	0.73***
811	0.23***	0.56***
812	0.25***	0.61***
813	0.18***	0.38***
821	0.02	0.82***
822	0.26	1.34***
823	0.01	0.98***
829	0.13	1.01***
853	0.48	0.11
855	0.21***	0.60***
856	0.71	0.29
861	-0.12	2.63***
862	0.81***	0.22
869	0.45***	0.47***
881	-0.22	1.25***
889	0.26*	0.52***
900	0.39***	0.50***
931	0.25***	0.63***
932	0.23*	0.79***
949	0.30	0.81*
951	0.32	1.07***
952	0.06	0.71***
960	0.58***	0.42***

Notes: *p<0.05; **p<0.01; ***p<0.001

Appendix D: Using labor market regions instead of municipalities

Table D.1: First step of the estimation

NOGA 3-digits (id and name)		Localization elasticity	Urbanization elasticity
Industries with the highest localization elasticities †			
949	Activities of other voluntary organizations	3.1330***	-1.9019***
421	Railways and roads construction	2.6340*	0.6393
464	Wholesale of domestic goods	2.0647***	-1.9018***
Industries with the smallest localization elasticities †			
782	Temporary-work agency activities	-1.2634***	2.4195***
732	Market research and public opinion polling	0.3657*	1.1491***
721	Physics and natural sciences R&D	0.3711***	0.3528
Industries with the highest urbanization elasticities †			
782	Temporary-work agency activities	-1.2634***	2.4195***
774	Intellectual property products leasing	0.1091	1.9484***
231	Glass and glassware products manufacturing	0.7846	1.8482*
Industries with the smallest urbanization elasticities †			
949	Activities of other voluntary organizations	3.1329***	-1.9019***
464	Wholesale of domestic goods	2.0647***	-1.9018***
663	Fund management	1.50717***	-1.4203***

Table D.2: Negative relationship between $\hat{\beta}_{loc}$ and $\hat{\beta}_{urb}$

	$\hat{\beta}_{loc}$ † †
Constant	0.9835***
	(0.0700)
$\hat{\beta}_{urb}$	-0.8050***
	(0.0918)
Observations	22
Adj. R^2	0.8515

Notes: *p<0.05; **p<0.01; ***p<0.001.

† Based on the estimated urbanization or localization elasticities with a minimum significance acceptance level of 5%.

† † Based on the estimated urbanization and localization elasticities jointly significant at a minimum significance acceptance level of 5%.

Robust standard errors in ( ).

Table D.3: Second step of the estimation ($\hat{\beta}_{loc}$)

	Estimated Localization Elasticities ($\hat{\beta}_{loc}$) †					
Constant	1.1900**	0.62056*	1.0520***	1.0011***	1.6310***	0.9792***
	(0.4438)	(0.2709)	(0.1412)	(0.0800)	(0.3028)	(0.0720)
Skill specificity index	1.0833^{+}	0.9133				
proxy for *labor market pooling*	(0.6042)	(0.5960)				
Education intensity	0.4053		-0.2071			
proxy for *knowledge spillovers*	(0.5408)		(0.3876)			
Manufactured inputs per CHF of sales	-0.0648			-0.1931		
proxy for *input sharing*	(0.6572)			(0.5656)		
Input dissimilarity index	-1.4979^{+}				-1.3034*	
proxy for *input sharing*	(0.8677)				(0.5737)	
Primary and energy inputs per CHF of sales	-2.0906					0.7366
proxy for *first nature agglo- -meration forces*	(2.6532)					(2.1062)
Observations	75	75	75	75	75	75
Adj. R^2	0.0266	0.0197	-0.0104	-0.0125	0.0401	-0.0131

Notes: $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001
† Based on the estimated urbanization elasticities with a minimum significance acceptance level of 5%. Robust standard errors in ( ).

Table D.4: Second step of the estimation ($\hat{\beta}_{urb}$)

	Estimated Urbanization Elasticities ($\hat{\beta}_{urb}$) †					
Constant	2.4673^{+} (1.2862)	1.7140*** (0.4038)	1.0918** (0.3652)	0.3333 (0.2242)	-0.0675 (1.0260)	0.4905* (0.1840)
Skill specificity index proxy for *labor market pooling*	-4.4138*** (1.0471)	-3.3302** (0.9556)				
Education intensity proxy for *knowledge spillovers*	-3.1040 (1.9386)		-1.9224 (1.1731)			
Manufactured inputs per CHF of sales proxy for *input sharing*	0.2062 (1.9485)			1.5602^{+} (0.8480)		
Input dissimilarity index proxy for *input sharing*	1.0088 (3.0708)				1.0963 (1.8248)	
Primary and energy inputs per CHF of sales proxy for *first nature agglo-* *-meration forces*	-0.0075 (3.4994)					2.7624 (3.2595)
Observations	41	41	41	41	41	41
Adj. R^2	0.2207	0.1248	0.04235	0.0242	-0.0143	-0.0221

Notes: $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001
† Based on the estimated urbanization elasticities with a minimum significance acceptance level of 5%. Robust standard errors in ( ).

Appendix E: Introducing the time dimension

Table E.1: Second step of the estimation ($\hat{\beta}_{loc}$)

	Estimated Localization Elasticities ($\hat{\beta}_{loc}$) †					
Constant	1.2879** (0.4331)	0.6700** (0.2709)	1.1116*** (0.1457)	1.0380*** (0.0892)	1.6833*** (0.2899)	1.0127*** (0.0754)
Skill specificity index proxy for *labor market pooling*	0.9496+ (0.5638)	0.8778+ (0.5245)				
Education intensity proxy for *knowledge spillovers*	0.2760 (0.5307)		-0.2779 (0.3946)			
Manufactured inputs per CHF of sales proxy for *input sharing*	-0.0036 (0.6712)			-0.1822 (0.5896)		
Input dissimilarity index proxy for *input sharing*	-1.4395 (0.8732)				-1.3225* (0.5571)	
Primary and energy inputs per CHF of sales proxy for *first nature agglo- -meration forces*	-1.6570 (2.8507)					1.1049 (2.3144)
Observations	79	79	79	79	79	795
Adj. R^2	0.0259	0.0195	-0.0070	-0.0119	0.0443	-0.0116

Table E.2: Second step of the estimation ($\hat{\beta}_{urb}$)

	Estimated Urbanization Elasticities ($\hat{\beta}_{urb}$) †					
Constant	2.5564* (1.0345)	1.7471*** (0.3912)	0.9580** (0.3610)	0.2493 (0.2418)	-0.1304 (0.8805)	0.4407* (0.1906)
Skill specificity index proxy for *labor market pooling*	-5.3634*** (1.1670)	-3.5860*** (0.9884)				
Education intensity proxy for *knowledge spillovers*	-3.6058+ (1.9060)		-1.6491 (1.1710)			
Manufactured inputs per CHF of sales proxy for *input sharing*	0.4655 (1.8811)			1.8462+ (0.9218)		
Input dissimilarity index proxy for *input sharing*	1.4921 (2.8658)				1.1324 (1.5371)	
Primary and energy inputs per CHF of sales proxy for *first nature agglo- -meration forces*	1.5411 (3.5364)					3.4815 (3.5151)
Observations	40	40	40	40	40	40
Adj. R^2	0.2858	0.1322	0.0254	0.0372	-0.0121	-0.0211

Notes: $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001
† Based on the estimated urbanization elasticities with a minimum significance acceptance level of 5%. Robust standard errors in ( ).

Appendix F: Time consistency of the estimates

Table F.1: Localization and urbanization estimates over time

NOGA	Localization Elasticities ($\hat{\beta}_{loc}$)			Urbanization Elasticities ($\hat{\beta}_{urb}$)		
1,2-digits	2005	2008	2011	2005	2008	2011
10-12	0.021	-0.0897	-0.0471	0.7979 ***	0.8012 ***	0.8043 ***
13-15	0.0077	0.0825	-0.0398	1.0623 ***	0.8519 ***	0.8789 ***
16-18	0.1764 ***	0.0262	0.0994	0.4969 ***	0.5968 ***	0.5645 ***
19-20	-0.0104	0.0101	0.0666	0.9327 ***	0.9526 ***	0.9504 ***
21	0.0323	0.2475	0.0392	1.7521 ***	0.8862 ***	1.1491 ***
22-23	0.0281	1e-04	0.1908	0.8606 ***	0.6944 ***	0.4538 ***
24-25	0.2256 ***	0.2272 ***	0.2342 ***	0.433 ***	0.4743 ***	0.4092 ***
26	0.4275 ***	0.3972 ***	0.3157 ***	0.4926 ***	0.5899 ***	0.5379 ***
27	0.0917	0.1991	0.04	0.6461 ***	0.8799 ***	0.8209 ***
28	0.1377 *	0.0986	0.1097	0.722 ***	0.7279 ***	0.5502 ***
29-30	0.1597	0.2649 *	0.3588 ***	0.5448 ***	0.6102 ***	0.4907 ***
31-33	0.196 ***	0.0414	0.0858	0.7321 ***	0.7487 ***	0.6857 ***
35	0.1253	0.0707	-0.0009	0.8166 ***	0.7787 ***	0.7713 ***
36-39	0.0729	0.135	-0.2127	0.7252 ***	0.7137 ***	1.0159 ***
41-42	0.008	0.0478	0.0789 *	0.774 ***	0.7471 ***	0.7497 ***
43	0.4606 ***	0.4979 ***	0.405 ***	0.4086 ***	0.4017 ***	0.4495 ***
45	0.304 ***	0.3901 ***	0.3509 ***	0.5125 ***	0.3868 ***	0.3806 ***
46	0.3492 ***	0.2764 ***	0.3577 ***	0.5855 ***	0.6766 ***	0.5769 ***
47	0.3868 ***	0.3148 ***	0.2265 ***	0.5723 ***	0.6278 ***	0.6561 ***
49	0.1107 *	0.1012 *	0.1656 ***	0.7514 ***	0.9104 ***	0.7027 ***
50-51	0.3852 ***	0.5695 ***	0.5761 ***	0.6522 ***	0.6002 ***	0.6711 ***
52	0.0914	0.1754 ***	0.0873	0.8948 ***	0.8607 ***	0.9637 ***
53	0.2886	0.181	0.5585 ***	0.6777 *	0.7145 ***	0.4155 *
55	0.417 ***	0.3071 ***	0.2954 ***	0.1356	0.1958 *	0.2595 ***
56	0.3341 ***	0.3791 ***	0.2322 *	0.6384 ***	0.4995 ***	0.682 ***
58-60	0.4358 ***	0.2701 ***	0.265 ***	0.5469 ***	0.729 ***	0.7049 ***
61	0.2564 *	0.1091	-0.0505	0.848 ***	1.1887 ***	1.0426 ***
62-63	0.3924 ***	0.4751 ***	0.3231 ***	0.5204 ***	0.4229 ***	0.6066 ***
64	0.5149 ***	0.397 ***	0.4012 ***	0.6351 ***	0.7517 ***	0.6166 ***
65	0.4447	-0.1851	-0.8407 *	0.5831	1.361 ***	3.4914
66	0.7574 ***	0.6721 ***	0.6096 ***	0.2416 ***	0.2996 ***	0.3953 ***
68	0.4651 ***	0.4057 ***	0.3962 ***	0.3799 ***	0.446 ***	0.4325 ***
69	0.6616 ***	0.607 ***	0.5804 ***	0.2564 ***	0.3266 ***	0.3467 ***
70	0.442 ***	0.4403 ***	0.4655 ***	0.4573 ***	0.4577 ***	0.3867 ***
71	0.3173 ***	0.3535 ***	0.2872 ***	0.5857 ***	0.517 ***	0.5688 ***
72	0.286 ***	0.2241 ***	0.2003 ***	0.8167 ***	0.9043 ***	0.86 ***
73-75	0.3398 ***	0.3516 ***	0.4687 ***	0.6545 ***	0.6368 ***	0.4744 ***
77+79-82	0.244 ***	0.2857 ***	0.3197 ***	0.6111 ***	0.5282 ***	0.4771 ***
78	0.3432 ***	0.2233 ***	0.1687 ***	0.6823 ***	0.8429 ***	0.7928 ***
85	0.332 ***	0.3367 ***	0.2897 ***	0.5992 ***	0.5417 ***	0.5171 ***
86	0.2274 ***	0.1951 ***	0.3515 ***	0.7204 ***	0.736 ***	0.566 ***
87	-0.067	-0.0437	-0.0015	0.6949 ***	1.4774 ***	0.5814
88	0.2759 *	0.2158 *	0.2915 ***	0.6019 ***	0.6626 ***	0.5048 ***
90-93	0.3075 ***	0.2701 ***	0.3469 ***	0.5977 ***	0.639 ***	0.5522 ***
94-96	0.3153 ***	0.2993 ***	0.4192 ***	0.7203 ***	0.6896 ***	0.5229 ***

Notes: *p<0.05; **p<0.01; ***p<0.001

† Each year refers to the employment data used. For example, for the estimation of $\hat{\beta}_{loc}$ of 2005 I used empl. data of 2005 and keep new firms created over the years 2006,2007 (see section 5.3).

Chapter 4

The Spatial Mismatch Between Income and Production: An Analysis on Swiss Municipalities *

1 Introduction

In a small area like Switzerland, with large commuting opportunities, income does not necessarily end up where it is created. Firms' and households' location choices are obviously linked, but they are motivated by different factors. Typically, firms tend to cluster due to agglomeration economies and households due to income sorting. These forces have important policy implications and have been consequently addressed by New Economic Geography models. Key parameters have been identified, such as commuting and trade costs, but as often, the final equilibrium patterns depend on the parameter values, which opens the field to empirical studies.

---

*This paper is co-authored by Joséphine Leuba (University of Neuchâtel, Faculty of Economics and Business).

The present study describes the spatial mismatch between production and income in Switzerland. We gather and combine data on income, value-added and employment at the municipal level. We find several empirical confirmations of spatial specialization. First, Theil index decompositions show that spatial disparities exist and come mainly from within-canton inequalities, confirming that the location process takes place at the municipal level. Second, series of plots and maps show that income and value-added are differently distributed across space. Third, we identify that the Swiss economic landscape is characterized by "productive" centers being surrounded by "residential" belts. These patterns are consistent with NEG models, in particular the framework developed by Borck et al. (2009), which constitutes our theoretical benchmark.

The spatial mismatch between production and income has important implications in terms of efficiency and equity across regions. On the one hand, the issues of transport, congestion and commuting costs arise when jobs and residences are not located in the same place. This involves externalities and public goods issues that may be at the origin of substantial welfare losses. On the other hand, it is hard to avoid the question of the spatial distribution fairness, especially regarding municipalities where wealth is produced, but where income is fleeing from. The tax base and the ability to spend money at the local level crucially depend on the type of economic activity implemented in a particular area, whereas public investments influence in turn the possibility of regional development. Thus, our empirical results should be of interest for the ongoing negotiations on fiscal equalization and geographical equity among Swiss municipalities and cantons.

After an overview of the current relevant literature, this chapter presents the data used, the empirical framework and the results. Before coming to its conclusion, the chapter presents also some robustness checks.

2 Literature Review

New Economic Geography (NEG)

We are interested in what makes a region rich or poor, so that we have to explore the attraction forces behind income and production. The concentration of income arises because households sort themselves. The model of Tiebout (1956) shows how heterogeneity of preferences and combinations of taxes and public goods leads to a sorted equilibrium in a federal state. Oates (1969) highlights the role of properties value in reinforcing the sorting process. Brueckner et al. (1999) underlines the role of amenities, arguing that a nice natural, cultural and historical environment is a luxury good. In a federalist state, we should therefore observe a concentration of rich people in nice places, where taxes are low and housing prices are high. In Switzerland, the role of taxation has been widely explored, including Schmidheiny (2006), Stadelmann and Billon (2012) and Schaltegger et al. (2011).

On the production side, since the seminal work of Marshall (1920), the empirical literature has firmly established that industries benefit from spatial concentration through productivity gains. But what hides beyond agglomeration economies? A useful preliminary step towards answering, as described by Rosenthal and Strange (2004), is to tell the difference between localization economies on the one hand, resulting from the spatial concentration of a specific industry, and urbanization economies on the other hand, resulting from the spatial concentration of economic activity as a whole. This fundamental distinction is now widely accepted in the literature.

To analyse firms' and households' locations together, the New Economic Geography (NEG) has developed very fertile frameworks. The seminal paper by Krugman (1991) presents a general equilibrium framework, where households and firms make simultaneous choices. Because of Marshallian externalities, firms locate where other firms are. Since workers follow job opportunities, and because workers are consumers, it creates an additional local demand, which attracts new firms. Muth (1971) and Mazek and Chang (1972) already pointed out this chicken or egg puzzle. Concentration arises, until congestion costs cancel out the advantage of proximity.

More recently, the NEG literature has produced several comprehensive formalizations of why economic agents tend to agglomerate (see e.g. Fujita et al. (1999), Fujita and Thisse (2002), Baldwin et al. (2005), Behrens et al. (2014)). This field has also evolved towards quantitative modelling, similarly to the earlier evolution of the trade literature (see e.g. Eaton and Kortum (2002)). The most recent models aim, in particular, to a better fit with the observed data (see e.g. Allen and Arkolakis (2014) or Caliendo et al. (2017)). In explaining localization choices, this literature highlights the distinction between "first nature" factors (physical endowments) and "second nature" factors (agglomeration forces through externalities). A large empirical literature has emerged in order to deepen our understanding of these "second nature" factors.

Given our research question, an important limitation of these NEG models is the no-commuting assumption: workers usually have residence and job in the same region, for simplification concerns. The theoritical model by Borck et al. (2009) is a notable exception. The authors combine the agglomeration economies assumption of Krugman (1991) with the housing market modelling of Helpman (1998). In the case of low commuting and transport costs, they find that the equilibrium involves concentration of firms and dispersion of households at the same time. Our paper is an empirical exploration of the processes involved in the model of Borck et al. (2009), which is presented in more details below.

Income vs GDP

At the macroeconomic level, the spatial mismatch between value creation and earnings is nothing but the distinction between product and income. Most macro-economic studies on spatial issues (growth, inequality, convergence between regions,...) focus on GDP (e.g. Gallo and Ertur (2003), Crozet (2004), López-Bazo et al. (2004)). However, since workers and capital cross borders, GDP is an imperfect indicator of the earnings of residents. The well-known Stiglitz report (Stiglitz et al., 2007) makes clear that the depreciation of capital, the balance of primary incomes and the evaluation of public expenditure should be taken into account when we evaluate the economic performance of a country. Its first recommendation is to use national income as an indicator, rather than GDP.

Using income instead of GDP makes a difference regarding distributional issues. Milanovic (1999) measures world inequality by using income data rather than GDP per capita and finds larger indicators of cross-country inequality. Martin (2009) describes inequality between European regions using the two measures. He finds that in France, spatial inequalities are larger if they are measured by GDP than by income, while in the UK, the reverse is true.

Most of the evidence so far regarding differences between the spatial distribution of income and production has been gathered at the macro level. Within-country empirical studies are more scant (e.g. Lee and Lin (2017) for the US or Geary and Stark (2016) for Great Britain). The present paper takes advantage of the availability of income and value-added data at the level of Swiss municipalities to perform for the first time a systematic analysis within that country.

Theoretical Model

We borrow the theoretical framework from Borck et al. (2009). They present a model which has two important features for our problematic. First, it is a general equilibrium model that makes endogenous the location of both firms and households, a common characteristics of NEG models. Second, and more innovatively, the model allows for commuting. Authors recognize that agglomeration economies drive the location decisions of firms (Krugman, 1991), but they also account for the importance of the housing market in the choice of residence (Helpman, 1998).

The general setup consists of two regions, with L units of land. There are two sectors:

- Industry (X), which is characterized by increasing returns to scale, monopolistic competition and iceberg trade costs. Industry employs skilled and unskilled workers.
- Agriculture (A), which is characterized by constant returns to scale, perfect competition and tradable goods without any transport costs. Agriculture only needs unskilled labour.

Unskilled workers are mobile between sectors but immobile between regions. The reverse is true for skilled workers. Borck et al. (2009) assume a quasi-linear utility function for individuals, which depends on their consumption of X, A and L. Agents solve the maximisation problem in three stages: first workers choose the place of residence, then skilled workers choose whether they commute or not, third, individuals choose how much they work and consume. In the long run, the utility level should be the same in every regions (so that nobody wishes to migrate), population and workforce are therefore endogenously determined.

Borck et al. (2009) present their predictions in three cases: prohibitive commuting costs, zero commuting costs and positive but non-prohibitive commuting costs. For given preference parameters and available land in each region, the location choices of firms and households, as well as the commuting patterns, are determined only by the degree of trade freeness. In particular, in the (most realistic) case of non-prohibitive commuting costs, the equilibrium involves concentration of firms and dispersion of households when the degree of trade freeness is high. On the contrary, households tend to concentrate and firms to disperse when transport and trade costs are high.

Applying these conclusions to Swiss municipalities, activities with a high degree of trade freeness like manufacturing should concentrate in municipalities that offer opportunities of agglomeration economies. The skilled and mobile workers tend to choose a residence location in a neighbouring municipality, from where commuting distance is not prohibitive and where the housing market is not congested. We therefore expect the formation of productive centers with high value-added, surrounded by a belt of municipalities hosting the skilled labour force.

On the other hand, the development of sectors with high transport costs is a concentration force for households and a dispersion force for firms. It is reflected by local services being spread everywhere and taking a higher share in the creation of value in the "residential" type of municipalities. It also results in urban centers attracting households in spite of high housing rents. Cities provide local services, that are not substitutable with what surrounding municipalities can offer.

3 Data

We use two data sources: the Federal Tax Administration (FTA) and the Federal Statistical Office (FSO).

Income Data

Income data come from the FTA. They are calculated on the basis of Federal Direct Tax returns (see Administration Fédérale des Contributions (2013)). The dataset contains annual average and total income in each municipality, in net and taxable terms.[1] The average is calculated per taxpayer (per household). These data have been initially gathered thanks to the SNF project "The Swiss Confederation: A Natural Laboratory for Research on Fiscal and Political Decentralization", led by Marius Brülhart, Monika Bütler, Mario Jametti and Kurt Schmidheiny from 2010 to 2016.

[1] *Net* income is the income after having removed insurance and savings interests. *Taxable* income is about 30% lower than the net income, as it excludes all the fiscal deductions.

Value-added Data

Data on value-added are derived from the WS survey database of the FSO[2] over the period 2011-2015. Due to confidentiality and feasibility constraints, we are forced to use data aggregated at the "pseudo-firm" level. A "pseudo-firm" is characterized by one municipality, one 4-digits NOGA sector and one legal form. In the process of data gathering, we need to address two major issues: first, due to the survey structure of the WS, some firms have missing values for given years. Indeed, 20% of the firms are replaced every year (this roll-over concerns in particular small firms) and some others simply do not respond. Secondly, in the context of our study, we are interested in the location of the productive unit rather than in the location of the administrative unit. In other words, plant level data are more adapted than firm level data. To tackle both issues, multiple imputation techniques are used and extensively described in Chapter 1. This methodology generates a total of 400 datasets, each being composed by the same "pseudo-firms" (whose creation relies on the same plants) but with different imputed value-added figures. In this study, we perform the analysis on each of these datasets and consider both the average results and the uncertainty around the imputed values.

Employment Data

In addition to the two mentioned datasets, we also gather data on employment using the STATENT census[3] database from the FSO. STATENT is used to create the 400 datasets of value-added (see Chapter 1) and to derive total employment (in full-time equivalent) in each municipality.

4 Empirical Framework

The Production/Income ratio

We aim to express the relative value-added created in one municipality compared to the amount earned by its residents. We need a simple statistic that translates the mismatch between production and income by municipality. The

[2] "Statistique de la Valeur Ajoutée - OFS". This survey excludes the primary sector and the banking and financial services sector.

[3] "Statistique Structurelle des Entreprises"

most evident indicator is the ratio between these two variables:

$$\text{ratio} = \frac{\text{VA}}{\text{INC}}$$

where VA stands for value-added and INC for income.

If the ratio is larger (smaller) than the Swiss average ratio, the municipality produces, relative to income, more (less) wealth compared to most other municipalities. We are therefore able to identify easily "productive" and "residential" municipalities. The distribution of this ratio is extensively described in section 5.

Theil decompositions

We first perform an analysis of the spatial dispersion of the value-added to income ratio. As mentioned above, there are two main processes at work leading to disparities between municipalities, both in terms of value-added and income, not only in levels but also in per capita (or per household) terms. Productivity inequalities are due to Marshallian externalities: firms tend to agglomerate in productive centers. Average income inequalities come from the sorting process: rich households tend to concentrate in nice places where taxes are low and housing rents are high. Moreover, both variables interact: firms are interested in locating near workers and consumers pools. Meanwhile, consumption opportunities matter in the households' choice of residence.

To quantify these two effects and their interaction, we perform a Theil decomposition.[4] In particular, the Theil index of the ratio (noted T_r) can be decomposed into net contributions of per household value-added (noted v), of the inverse of average income per household (noted y) and of the interaction between the two (noted Ω). With $\bar{x}$ being the average of any variable x, the

[4]We thank Jean-Marie Grether to have suggested that decomposition.

decomposition can be expressed as follows:[5]

$$T_r = \gamma T_v + \gamma T_y + \Omega$$

where,

$$r = v \cdot y$$
$$\Omega = \ln\gamma + \gamma\Big(cov(\frac{v_i}{\bar{v}}\ln(\frac{v_i}{\bar{v}}), \frac{y_i}{\bar{y}}) + cov(\frac{y_i}{\bar{y}}\ln(\frac{y_i}{\bar{y}}), \frac{v_i}{\bar{v}})\Big)$$
$$\gamma = 1 - \frac{cov(v, y)}{\bar{r}}$$

This first decomposition shows how the spatial economic disparities in the value-added-to-income ratio come from agglomeration economies on the one hand, and from the income sorting process on the other hand.

In order to investigate if the location process of firms and households takes place more at the municipal level than at the cantonal one, we perform a second decomposition. In particular, we separate the Theil index into the usual within and between components for any subgroup:

$$T_r = \underbrace{\sum_{j=1}^{M} s_j \cdot T_{r_j}}_{within} + \underbrace{\sum_{j=1}^{M} s_j \cdot \ln(\frac{\bar{r}_j}{\bar{r}})}_{between}$$

where,

M is the number of cantons

$s_j = \frac{N_j \bar{r}_j}{N\bar{r}}$ with N_j being the number of observations in canton j

This second decomposition gives indications on the role of cantonal policies and the importance of distance-related costs in the location model. Notably, the within-cantons variation corresponds to the low commuting cost case described in section 2. The between inequality indicator will reflect to what extent cantons are also able to specialize. Inequality in the ratio may be particularly salient between small cantons (in surface area) like Geneva at one extreme (high ratio),

[5] See the development in technical Appendix B. r is equivalent to our ratio in the previous subsection, since the numerator and denominator are divided by the same factor. The reason of using per capita terms in this decomposition is to abstract from the scale effect.

and Schwyz at the other (low ratio).

These two decompositions can be run separately to investigate the driver of spatial inequality in the value-added-to-income ratio. Is it the spatial inequality in per capita value-added, average income or their interaction (first decomposition)? Or is it rather due to intra- or inter-cantonal inequalities (second decomposition)? The two decompositions can also be run jointly. This gives rise to the two-way matrix decomposition represented by Table 1.[6]

Table 1: Two-way Matrix decomposition.

	v	y	$Cov.$	Total
Within	$\sum_{j=1}^{M} s_j \gamma_j \frac{\bar{y}}{\bar{y}_j} T_{v_j}$	$\sum_{j=1}^{M} s_j \gamma_j \frac{\bar{v}}{\bar{v}_j} T_{y_j}$	$\sum_{j=1}^{M} s_j \Omega_j$	$\sum_{j=1}^{M} s_j T_{r_j}$
Between	$\sum_{j=1}^{M} s_j \frac{\gamma_j}{\gamma} \frac{\bar{y}}{\bar{y}_j} \ln\left(\frac{v_j}{\bar{v}_j}\right)$	$\sum_{j=1}^{M} s_j \frac{\gamma_j}{\gamma} \frac{\bar{v}}{\bar{v}_j} \ln\left(\frac{y_j}{\bar{y}_j}\right)$	$\sum_{j=1}^{M} s_j \Theta_j$	$\sum_{j=1}^{M} s_j \ln\left(\frac{\bar{r}_j}{\bar{r}}\right)$
Total	γT_v	γT_y	Ω	T_r

Where the within and between interaction terms, Ω_j and Θ_j, are given by,

$$\Omega_j = \ln(\gamma_j) + cov\left(\frac{v_i}{\bar{v}} \ln\left(\frac{v_i}{\bar{v}}\right), \frac{y_i}{\bar{y}}\right) + cov\left(\frac{y_i}{\bar{y}} \ln\left(\frac{y_i}{\bar{y}}\right), \frac{v_i}{\bar{v}}\right) + \left[1 - \frac{\bar{y}}{\bar{y}_j}\right] \frac{\gamma_j}{\gamma} T_{v_j} + \left[1 - \frac{\bar{v}}{\bar{v}_j}\right] \frac{\gamma_j}{\gamma} T_{y_j}$$

$$\Theta_j = \ln\left(\frac{\gamma}{\gamma_j}\right) + \left[1 - \frac{\bar{y}}{\bar{y}_j}\right] \frac{\gamma_j}{\gamma} \ln\left(\frac{v_j}{\bar{v}_j}\right) + \left[1 - \frac{\bar{v}}{\bar{v}_j}\right] \frac{\gamma_j}{\gamma} \ln\left(\frac{y_j}{\bar{y}_j}\right)$$

Spatial analysis of the Production/Income ratio

We characterize the dispersion of the ratio across space using visualization tools such as plots, maps and Moran scatter plots. In addition, we present the correlations between our ratio and the distribution of employment across industries. We should find higher ratios in municipalities where agglomeration economies are important (see Chapter 3). On the contrary, the ratio lower in "residential" municipalities that attract rich people, and where local services are overrepresented (see Leuba (2019)).

[6]See technical Appendix B for the detailed demonstration.

5 Results

Table 2 presents the summary statistics of the main variables. Value-added is higher than net income on average as we observe the mean of the ratio being between 1.29 and 1.33. This should not come as a surprise for two reasons. First, due to data availability limitations, we use "gross" value-added rather than "net" value-added. The difference between the two represents the capital depreciation, which cannot be redistributed as income in the economy. Using "gross" value-added therefore overestimates the value creation and, consequently, the ratio. According to Swiss National Accounts statistics, the capital depreciation, relative to "gross" value-added, was 20.8% on average over the years 2011-2015.[7] Second, the ratio being larger than one also reflect the firms' earnings that are not redistributed to shareholders.

There is high variability across space, the minimum corresponds to the municipality Petit-Val (BE) and the maximum to Manno (TI). Variances are relatively large, with a standard deviation of the ratio exceeding the mean for all variables. It can be shown that the distribution of the production/income ratio is skewed to the left.[8]

Value-added and income seem quite stable over time. The same comment holds for the standard deviation, except for income (and consequently the ratio) in 2014. The increase in the variance is drawn by outliers, typically small municipalities like Anières, which became ten times richer in 2014 because one extremely rich taxpayer settled in the jurisdiction.

[7] Own calculation based on the Swiss National Accounts statistics (see https://www.bfs.admin.ch/bfs/fr/home/statistiques/economie-nationale/comptes-nationaux/sequences.html). Further calculations show that capital depreciation relative to "gross" value-added was equal to 22.2% for non-financial companies (S11), 11.2% for financial companies (S12) and 27.1% for public administrations (S13) on average over the years 2011-2015.

[8] The entire distribution of the ratio can be found in Figure A.3.

Table 2: Summary statistics

Variable	Year	Mean	Min	Median	Max	St. Dev.
Value-added*,†	2011	340272.72	37.78	63807.79	47476244.85	1818879.89
		(64.45)	(0.86)	(57.30)	(32364.37)	(988.54)
	2012	332016.30	30.27	61706.12	45802739.79	1801187.84
		(62.34)	(0.25)	(51.18)	(31786.18)	(957.75)
	2013	337518.58	46.75	63022.46	46491096.11	1786180.25
		(72.49)	(1.42)	(51.21)	(34804.81)	(1134.48)
	2014	346478.18	4.09	65366.33	47531862.49	1814765.50
		(58.87)	(0.00)	(50.05)	(27177.25)	(973.66)
	2015	347554.75	89.63	63091.95	49037735.71	1908821.42
		(53.99)	(1.54)	(59.49)	(30587.50)	(1033.16)
Income†	2011	176731.76	3868.80	76061.78	16911838.19	582799.33
	2012	176515.85	3596.67	76646.63	16986498.63	581377.24
	2013	181161.47	3301.33	79046.47	1731009.11	595074.27
	2014	185285.87	3572.27	80346.07	17772252.31	612262.092
	2015	188478.43	3757.13	82155.08	18694467.63	632915.94
Nb. of households	2011	2736.45	62.00	1216.00	249257.00	8835.13
	2012	2750.76	64.00	1218.50	251287.00	8877.41
	2013	2797.35	57.00	1245.00	254108.00	9002.98
	2014	2819.83	61.00	1272.00	254158.00	9060.66
	2015	2868.15	65.00	1286.50	263358.00	9302.38
Ratio*	2011	1.3381	0.0010	0.8351	20.8182	1.8316
		(0.0007)	(0.0000)	(0.0005)	(0.1315)	(0.0028)
	2012	1.2754	0.0005	0.8045	20.0877	1.7521
		(0.0005)	(0.0000)	(0.0005)	(0.1083)	(0.0022)
	2013	1.2977	0.0008	0.8148	21.3009	1.8303
		(0.0006)	(0.0000)	(0.0007)	(0.1180)	(0.0023)
	2014	1.3253	0.0003	0.8001	25.2474	1.9236
		(0.0005)	(0.0000)	(0.0006)	(0.2726)	(0.0041)
	2015	1.2890	0.0010	0.7828	24.5699	1.8660
		(0.0006)	(0.0000)	(0.0006)	(0.0912)	(0.0021)

Notes:

* In parenthesis, the standard error of the given statistics mean (i.e. statistics are computed on each of the 400 datasets and the mean and standard deviation of the mean of each statistics are reported).

† In thousands of CHF.

Theil decompositions

Table 3 shows the decomposition of the Theil index for the last year of our sample.

Table 3: Two-way Matrix decomposition for 2015.

	VPH*	IPH*	Cov.	Total
Within	0.58941	0.01310	-0.03913	0.56338
	(0.01000)	(0.00002)	(0.00272)	(0.00845)
Between	0.04461	0.00779	-0.01838	0.03402
	(0.00250)	(0.00001)	(0.00132)	(0.00192)
Total	0.63402	0.02089	-0.05752	0.59739
	(0.01073)	(0.00003)	(0.00353)	(0.00878)

Notes: * VPH is value-added per household and IPH inverse of income per household.
See Table 1 for the analytical expressions of the decomposition.

Comparing the table's rows, the first lesson is that within-cantonal inequality is much larger than the between disparities. 92% of the value-added per household disparities and 63% of the income inequality take place at the municipal – not cantonal – level. The process of specialization occurs mainly at the municipal level, which corresponds to the low commuting and trade costs case of section 2.

Looking at the columns, we notice that value-added per household is far more uneven than average income. This holds within and between cantons. It appears that the forces which drive firms concentration dominate the ones behind income sorting of households. As predicted by the theoretical model, firms concentrate, while households spread when commuting (and trade) costs are low or non-prohibitive. The covariance component is negative because of the positive relationship between the average income and value-added per household.[9] Large cities are for instance richer both in term of income and value-added. Similar figures appear for the other years (Tables B.3 – B.6 in Appendix). The observed facts seem stable over time.

[9] Indeed, if the denominator tends to be large when the numerator is large, then the variability of the ratio is lower than if both variable are totally independent.

Spatial analysis of the Production/Income ratio

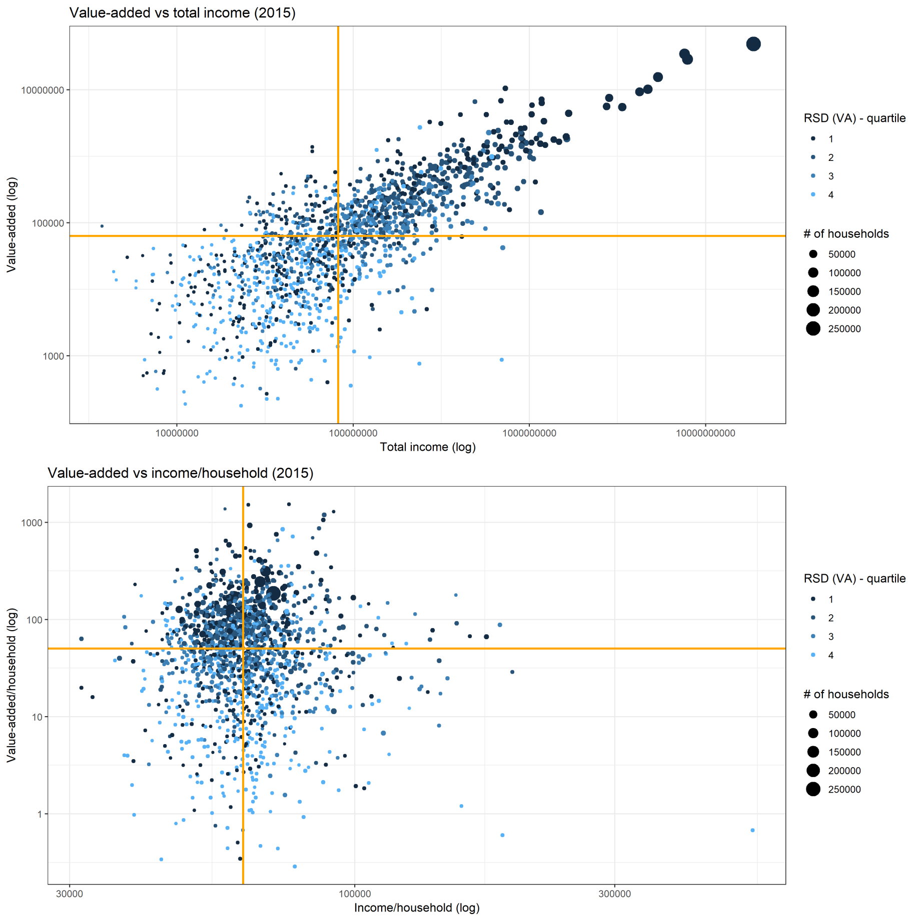
The first set of graphs shows how do the distributions of value-added and income differ in general. The results for 2015 are shown in Figure 1, whereas the same plots for 2011 are reported in the Appendix Figure A.1. On the top graph, the points tend to align on the diagonal, showing that the richer municipalities in terms of income are also the richer in value-added terms. This reflects the scale effect. A radically different picture appears on the second graph, when we get rid of the scale effect. The richest households do not necessarily live in the municipalities with the highest average production. However, the larger points lie in the upper-right part of each graph. This indicates that large urban centers attract both rich households (because of urban amenities, see Brueckner et al. (1999)) and productive firms (because of agglomeration economies).

Figure 2 shows the spatial distribution of the ratio in 2015. The maps representing ratio in the other years, as well as income and value-added are in Appendix, Figures C.1, C.2 and C.3.

The highest ratios are found in either dense populated areas (e.g. Geneva (GE), Zurich (ZH) , Basel (BS), Bern (BE)) or municipalities where sectors with high value-added are prominent. For instance, the tobacco and gold production in Neuchâtel (NE) and the watch industry in la Vallée de Joux (VD). Using the typology of Rosenthal and Strange (2004), the cities profit from urbanization economies, while the specialized municipalities are characterized by localization economies. By using data on employment, Chapter 3 has shown the importance of both effects in the Swiss economy. On average urbanization economies seem to be more important in Switzerland, which might be due to the relative high urban density of the country. Towns next to the borders tend to have high ratios as well (e.g. Le Locle (NE), Boncourt(JU) and Sennwald (SG)). In those areas, firms benefit from the labor pool located in other countries. The access to workforce is indeed one of the three types of Marshallian externalities, giving a relative advantage to the border regions.

Oppositely, the low-ratio municipalities are typically located in nice natural environment. For instance, the proximity of a lake is a prominent factor to attract rich households (e.g. the North of lakes Biel and Thun or the South of lakes Neuchâtel and Lucerne). This is in line with the work of Leuba (2019) on the impact of local amenities on household's location choices in Switzerland.

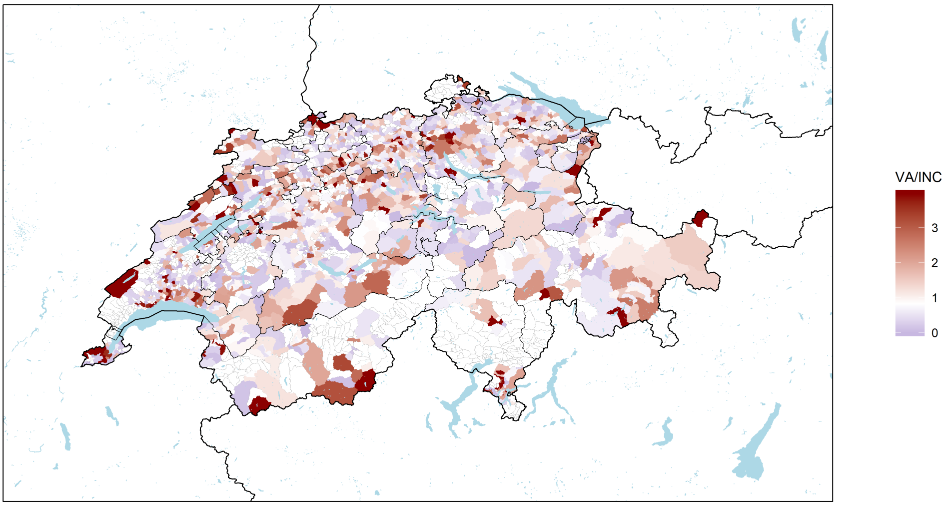
Figure 1: Income and value-added (total and per household) - 2015.



Note: value-added (vertical axis) and income (horizontal axis) are represented on a logarithmic scale. Orange lines are drawn at the median. The colour represents the relative standard deviation of value-added across the 400 databases. The darker the point, the lower the relative standard deviation.

Turning to the geographical interdependence between high- and low-ratio municipalities, we observe a pattern of "surrounding belts", as predicted by

Figure 2: Spatial distribution of the ratio VA/Income.

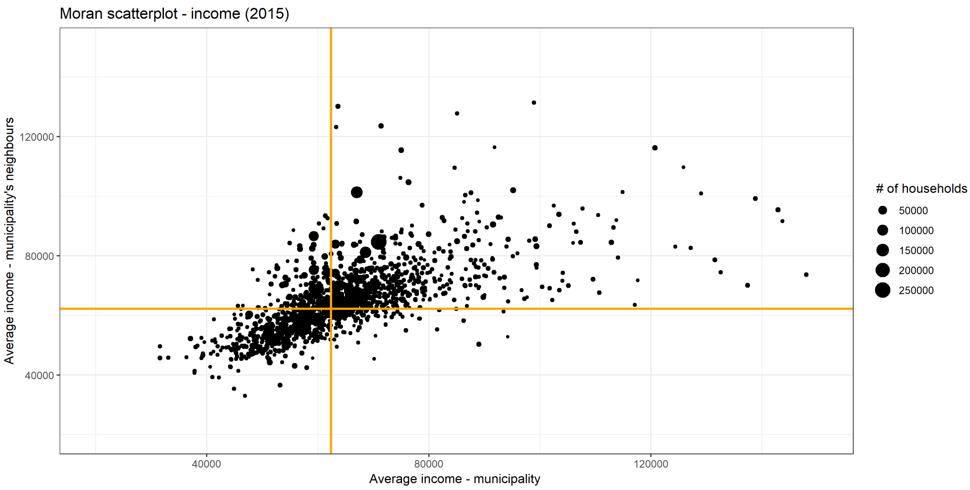


the theoretical model. With non-prohibitive commuting costs, skilled workers are dispersed where the housing market is less congested and into municipalities that offer valuable amenities (among which accessibility, see Leuba (2019)). This pattern can be observed around the largest cities such as Zurich (ZH), Basel (BS), Bern (BE), Lugano (TI) and Geneva (GE), but also around smaller productive centers such as Biel (BE), St-Imier (BE) or Monthey (VS).

The hypothesis of residential municipalities surrounding high-ratio units can be further explored with Moran scatterplots. The graph 3 represents the variable of interest in one municipality (horizontal line) plotted against the same variable found on average in the contiguous municipalities. The orange lines represent the median of each variable. We express income and value-added in per capita terms, in order to get rid of the scale effect. There is clear positive spatial autocorrelation in terms of income, with a slope of almost 1: one given municipality tends to be as rich as its neighbours. They indeed share many common characteristics (canton, natural environment, etc.).

However, we do not find such positive spillovers in the value-added per house-

Figure 3: Moran Scatterplot - Income per taxpayer.



hold. Again, in our model with positive commuting costs, productive firms concentrate in the same places. The absence of positive spatial autocorrelation indicates that this process takes place mainly at the scope of the municipality. The larger points (i.e. large municipalities) lie in the upper-right quadrant. Indeed, urbanization economies often cross the municipal borders in these cases (e.g municipalities around Lausanne, Basel and Zurich). The picture remains the same as we add the sectoral dimension. The Moran scatter plots representing productivity by NACE sectors in 2015 are available in Appendix C. We can not distinguish any positive relationship on none of these graphs.[10]

Positive autocorrelation seems also absent in the ratio, despite the spatial dependence of income. The graph is consistent with the "surrounding belt" pattern. The residential municipalities lie on the left and spread equally in the bottom and upper quadrant. This suggests that, they are surrounded by other residential municipalities (low ratio) and productive centers (high ratio) together. The points on the right, which tend to be larger, represent productive centers. Again, the part situated in the upper quadrant reflects productive centers that spill over the municipal frontiers.

[10]The same conclusion holds considering NOGA 3 sectors (results available upon request).

Figure 4: Moran Scatterplot - Value-added per household.

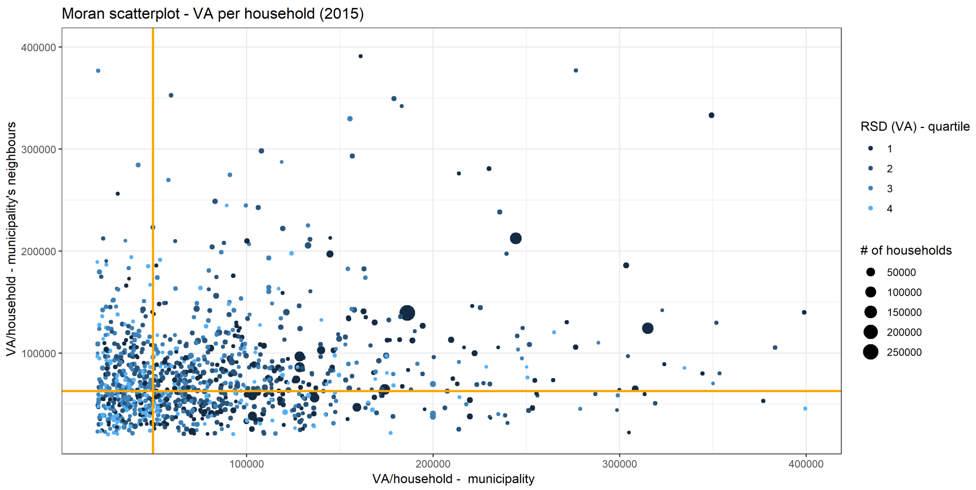
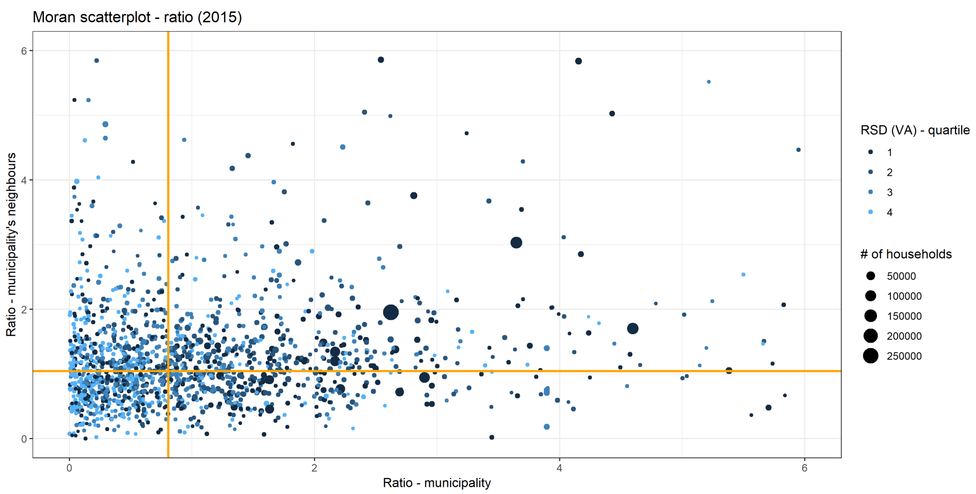


Figure 5: Moran Scatterplot - Ratio value-added/income.



Moran scatterplots are informative to highlight the "surrounding belt" pattern identified on the maps. It appears that, indeed, large productive centers are surrounded by residential municipalities. The former are likely to benefit from agglomeration economies, which depend on the industrial structure of the given municipality as shown by Chapter 3. That is why, we explore the link between the ratio and the industry specialization of a municipality in Table 4. We compute the share of employment (Share_{is}) in each industrial section per municipality.[11] Then we calculate the correlation between our ratio and the share of employment in each industry.[12]

Table 4: Correlation between the share of employment per industry and the VA/INC ratio.

Industrial classification (NACE)*		Year				
Code	Description	2011	2012	2013	2014	2015
2a	Manufacturing industries	0.10838	0.11929	0.11485	0.11064	0.11001
		(0.00754)	(0.00636)	(0.00567)	(0.00793)	(0.00597)
2	Extraction and other industries	-0.04667	-0.050790	-0.04591	-0.04903	-0.05064
		(0.00212)	(0.00212)	(0.00221)	(0.00270)	(0.00230)
3	Building sector	0.01580	0.00116	0.01300	0.03890	0.02643
		(0.00878)	(0.00614)	(0.00646)	(0.00938)	(0.00693)
4	Whole and retail sales, transport, hotels and restaurant, TIC	0.02190	0.02620	0.00798	-0.01130	0.00216
		(0.00748)	(0.00515)	(0.00593)	(0.00510)	(0.00676)
7	Real estate	-0.04923	-0.06047	-0.06960	-0.05287	-0.06297
		(0.01145)	(0.00358)	(0.00232)	(0.00352)	(0.00175)
8	Scientific and technical activities, administrative services	-0.034647	-0.02757	-0.00510	-0.00976	-0.01288
		(0.00321)	(0.00730)	(0.00428)	(0.00400)	(0.00415)
9	Public administration, defense, teaching, health and social activities	-0.12996	-0.12797	-0.12487	-0.12030	-0.11602
		(0.00364)	(0.00303)	(0.00317)	(0.00428)	(0.00251)
10	Other services	-0.07465	-0.07842	-0.07203	-0.07007	-0.07517
		(0.00243)	(0.00200)	(0.00221)	(0.00254)	(0.00206)

Notes: * Two NACE sectors are not covered by the value-added statistics: 1 (Agriculture, forestry and fishing) and 5 (Financial) services and insurances.
Each correlation is computed on the 400 datasets, the mean and standard deviation (in parenthesis) are reported.

At this industrial level we observe, in general, very low correlations, which are stable over time. Two exceptions are salient: the NACE section 2a (manufacturing) and NACE section 9 (public sector). The former is characterized by a relatively high and positive correlation, while the latter is especially negative. A region having an industrial structure biased (in terms of employment) towards manufacturing sector is associated with a high ratio. This municipality

[11] $\text{Share}_{is} = \text{FTE}_{is}/\text{FTE}_i$ where FTE_{is} is the number of full time-equivalents employed by sector s in municipality i and FTE_i is the total number of full time-equivalents in municipality i.

[12] Since part of the value-added is imputed and leads to 400 different value-added samples, we have 400 candidate ratios per municipality. Therefore, the above described correlation is computed on each sample and results are averaged across samples.

would therefore create more revenue than received. On the contrary, a region specialized in the public sector would be associated with a low ratio.

It is again in line with the predictions of the model presented in section 2: the manufacturing industry is characterized by a relatively high trade freeness and low transport costs, as evidenced by the relative importance of exports in this sector. On the contrary, public services are not easily transportable. Consider for instance health care. Family doctors, physiotherapists or residential care facilities are needed everywhere where households live. This sector is therefore overrepresented in the "residential" type of municipalities, in which the ratio is low.

The chosen level of industrial aggregation may appear too large. To investigate further, we perform the same exercise but at the industrial level NOGA 3. The results are presented in Appendix, Figure D.1. They confirm the above comments.

6 Robustness

The definition of income used in the paper is quite narrow: the municipality income is the sum of the residents' incomes. One could argue that the net benefits from firms might also be considered as a measure of municipality income.[13] To have a comprehensive view about spatial income distribution, we test this alternative measure of municipality revenue (i.e. adding firms' net benefits to households' incomes). Summary statistics are provided in Table 5.

[13] This measure overestimates total income, since dividends are counted twice.

Table 5: Summary statistics including net benefits

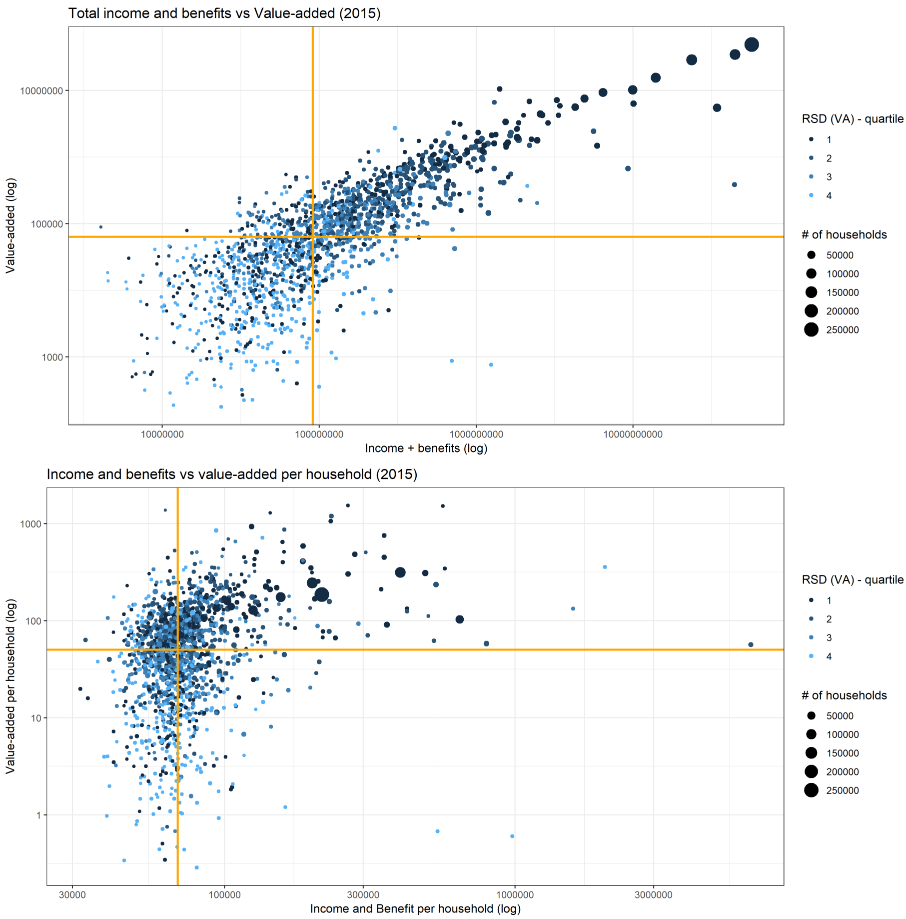
Variable	Year	Mean	Min	Median	Max	St. Dev.
Net benefit[†]	2011	139075.89	0.00	4565.65	48354630.30	1601382.13
	2012	120923.96	0.00	4871.95	27935717.20	1164915.41
	2013	129812.60	0.00	5262.50	29845486.80	1263686.38
	2014	144235.16	0.00	5598.15	36717571.90	1398765.85
	2015	190525.22	0.00	5407.50	43899735.90	2036326.27
Ratio, including benefits[*]	2011	1.0574	0.0010	0.7384	15.1419	1.2622
		(0.0006)	(0.0000)	(0.0005)	(0.1158)	(0.0027)
	2012	0.9980	0.0005	0.7137	14.1241	1.1596
		(0.0004)	(0.0000)	(0.0005)	(0.0730)	(0.0017)
	2013	1.0026	0.0007	0.7169	14.7068	1.1844
		(0.0005)	(0.0000)	(0.0006)	(0.0651)	(0.0015)
	2014	1.0141	0.0003	0.7082	18.6790	1.2332
		(0.0005)	(0.0000)	(0.0006)	(0.2929)	(0.0047)
	2015	0.9928	0.0005	0.6905	21.9602	1.2038
		(0.0005)	(0.0000)	(0.0005)	(0.0847)	(0.0021)

Notes: [*] In parenthesis, the standard error of the given statistics mean (i.e. statistics are computed on each of the 400 datasets and the mean and standard deviation of the mean of each statistics are reported).
[†] In thousands of CHF.

Adding net firms benefit to residents income reduces the ratio and its variance. Figures 6 and 7 confirm the trends already observed. Richer municipalities tend to produce more value-added, while no evident pattern emerges when getting rid of the scale effect (variables per household). This reinforces our previous findings: the most productive firms do not necessarily locate where the richest households live.[14]

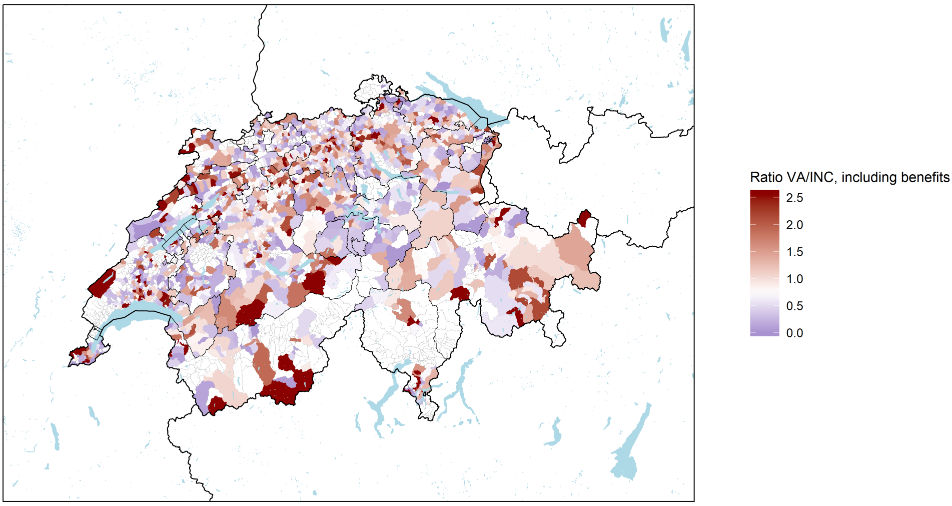
[14]The firms do not necessarily declare their benefits at the same place as they produce, either. See Figure A.2 in Appendix. We also re-perform the Theil decompositions, with no substantial change in the results.

Figure 6: Total income (including net benefits) and value-added (total and per household) - 2015.



Note: value-added (vertical axis) and total income (horizontal axis) are represented on a logarithmic scale. Orange lines are drawn at the median. The colour represents the relative standard deviation of value-added across the 400 databases. The darker the point, the lower the relative standard deviation.

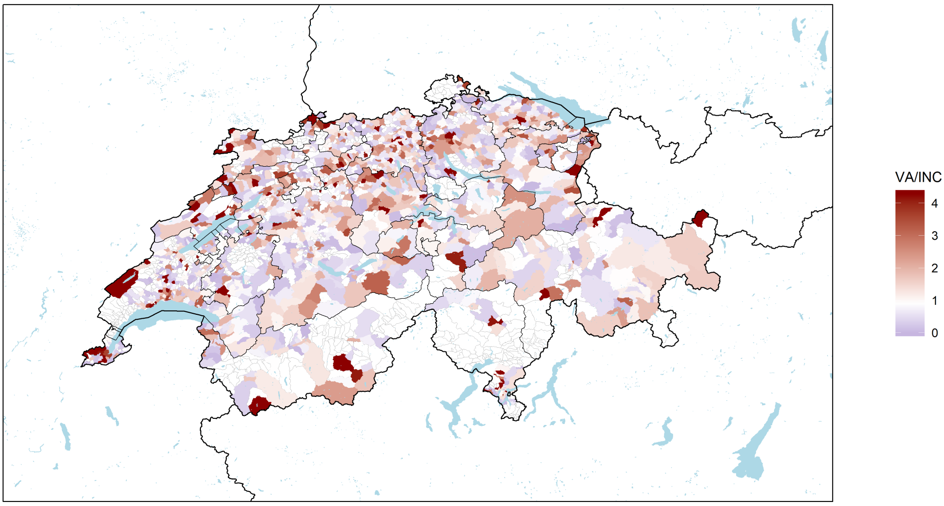
Figure 7: Spatial distribution of the ratio VA/INC, including benefits (2015).



In our study, we rely on the set of weights ("weights II") recommended in Chapter 1 to construct a representative sample. As a final robustness exercise, we replace these weights by the alternative set ("weights I"). The identified trends are verified. In particular, we keep on observing a "surrounding belt" pattern around urban centers.[15]

[15]Detailed results available upon request.

Figure 8: Spatial distribution of the ratio VA/INC, alternative weights definition (2015).



7 Conclusion

In this paper, we explore the spatial distribution of income and production across Swiss municipalities. Our results are in line with the equilibrium outcomes suggested by New Economic Geography models, such as the one presented in Borck et al. (2009). The model with low commuting costs seem suitable to explore the location process at the municipal level. Indeed, Theil decompositions show that spatial differentiation takes place at the municipal – rather than cantonal – level. We also note that value-added per household inequalities between municipalities are more pronounced than the average income disparities. The income sorting process, reinforced by the federalist structure of taxation and the adjustments on the housing market, is weaker than the concentration process of productive firms due to Marshallian externalities. Further analyses demonstrate a substantial spatial variability of the ratio between value-added and income. Municipalities attract productive firms or rich households to very different extents. The municipalities with the highest ratios are the ones in which there are agglomeration economies. On the other hand, the typical low-ratio municipality, where the share of local services is especially high, is situated near productive centers. Overall, our results confirm that when commuting costs are reasonably low, sectors with high degree of trade freeness tend to agglomerate, and residences of skilled workers tend to spread.

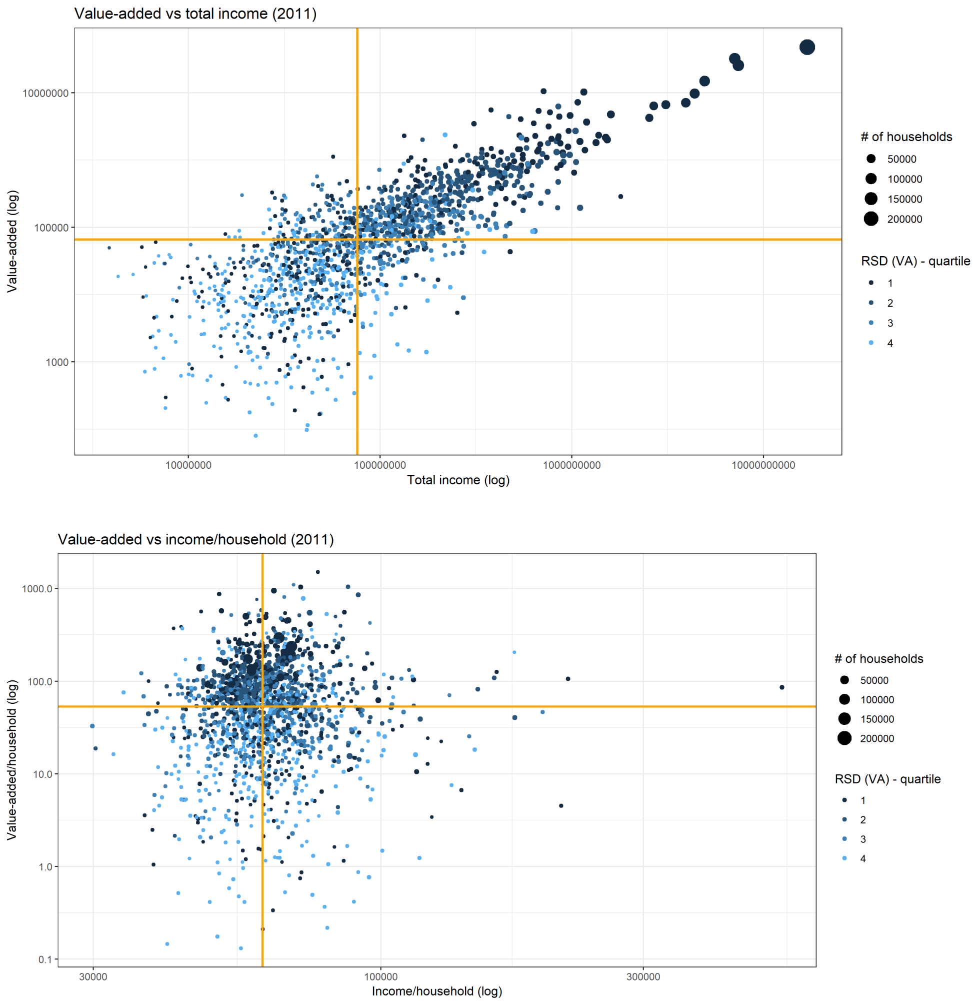
Our results suggest various policy recommendations. First, a decrease in commuting costs (by investing in transport infrastructure for example) reinforces the mismatch between productive and residential areas in the long run, increasing at the end the need for commuting. It is an issue because of externalities such as pollution or risks of accidents. In terms of collective welfare, reducing the gap between public and private costs of daily transport is therefore even more important than reducing the private commuting cost itself.

Second, the fiscal question comes naturally in mind, firstly because the tax system is highly decentralized. Tax competition reinforces the income and value-added sorting processes (rich municipalities are able to set lower tax rates, which will attract rich households and/or more firms). So, the fiscal system favours the spatial specialization of municipalities, even if some fiscal equalization schemes are put in place between and within cantons. Furthermore, our results show that a withholding tax (levied at the workplace rather than residence) would radically change the repartition of tax revenues among Swiss municipalities. We do not advocate for such a system, which would not be necessarily fairer (public spending depends on residents, probably more than on the number of jobs). We just point out the fact that rich and poor municipalities could be defined differently from what it is generally agreed (i.e. according to their current tax base). The location of production matters and should be carefully included into the negotiations about financial equalization. The efforts to compensate the excess burden on urban centers go into that direction (see Ecoplan (2017)), although the setoff is still partial.

Third, the economic specialization of municipalities occurs mainly within cantons. Thus, if there is some public action to be undertaken, it can already be done at the local level. Between-municipalities negotiations could potentially cover the main part of spatial economic disparities if they were successfully generalized in every canton.

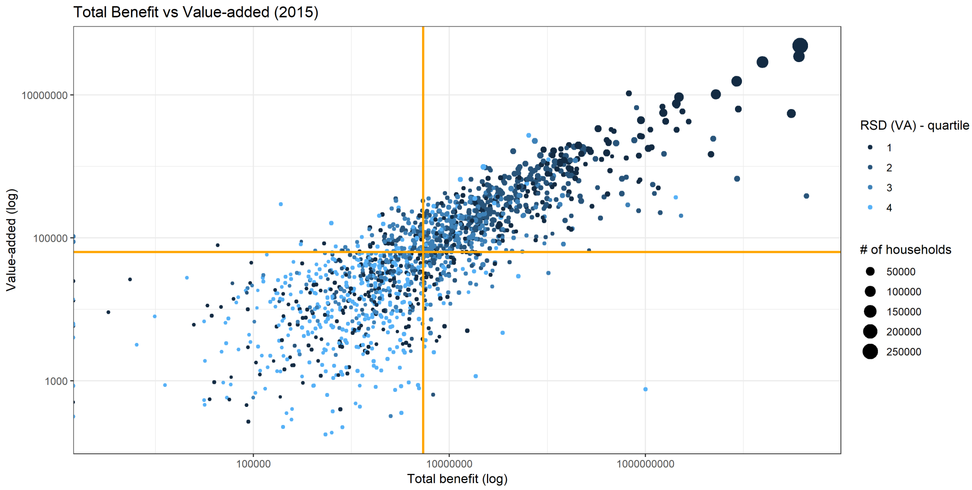
Appendix A: Ratio - descriptive statistics

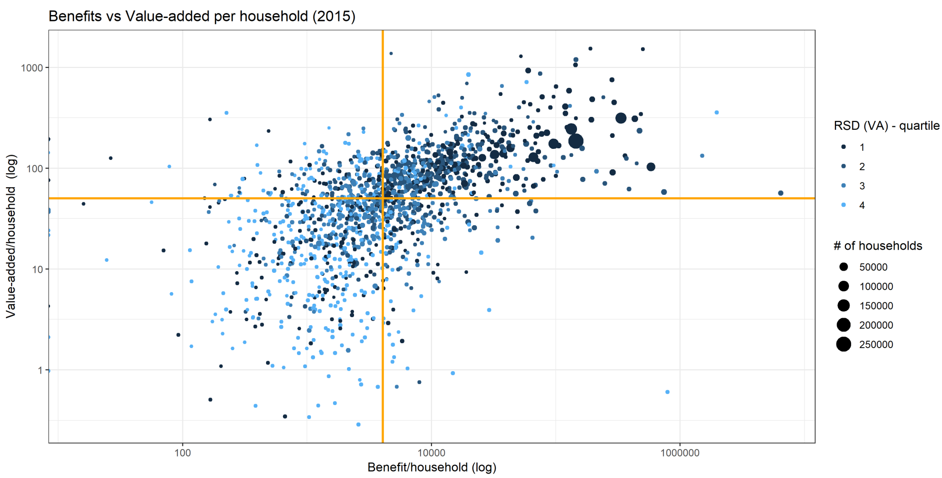
Figure A.1: Income and value-added (total and per worker) - 2011.



Note: value-added (vertical axis) and income (horizontal axis) are represented on a logarithmic scale. Orange lines are drawn at the median. The colour represents the relative standard deviation of value-added across the 400 databases. The darker the point, the lower the relative standard deviation.

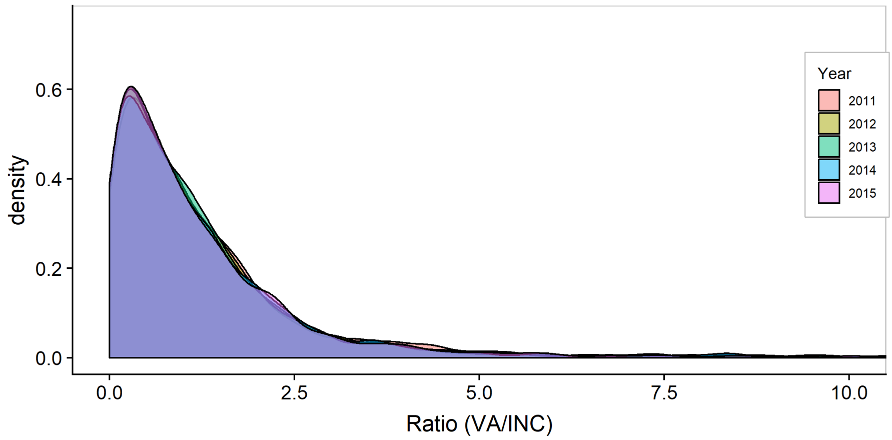
Figure A.2: Total benefit and value-added (total and per worker) - 2011.





Note: value-added (vertical axis) and benefit (horizontal axis) are represented on a logarithmic scale. Orange lines are drawn at the median. The colour represents the relative standard deviation of value-added across the 400 databases. The darker the point, the lower the relative standard deviation.

Figure A.3: Distribution of the ratio of interest, value-added over income 2011-2015.



Appendix B: Theil decompositions

The between-within decomposition

Notation: there are M cantons and N_j municipalities i in each canton j. The total number of municipalities is therefore given by $N = \sum_{j=1}^{M} N_j$. The share of canton j in the national total with respect to variable a is given by $s_j = \dfrac{N_j \cdot \bar{a}_j}{N \cdot \bar{a}}$. Where $\bar{a}$ is the national mean and $\bar{a}_j$ the mean in canton j. We have therefore:

$$
\begin{aligned}
T_a &= \frac{1}{N}\sum_{i=1}^{N}\frac{a_i}{\bar{a}} \cdot \ln\left(\frac{a_i}{\bar{a}}\right) \\
&= \frac{1}{N}\sum_{j=1}^{M} N_j \cdot \frac{1}{N_j}\sum_{i=1}^{N_j}\frac{a_i \cdot \bar{a}_j}{\bar{a}_j \cdot \bar{a}}\left[\ln\left(\frac{a_i}{\bar{a}_j}\right) + \ln\left(\frac{\bar{a}_j}{\bar{a}}\right)\right] \\
&= \sum_{j=1}^{M}\underbrace{\frac{N_j\bar{a}_j}{N\bar{a}}}_{s_j} \cdot \underbrace{\frac{1}{N_j}\sum_{i=1}^{N_j}\frac{a_i}{\bar{a}_j} \cdot \ln\left(\frac{a_i}{\bar{a}_j}\right)}_{T_{a_j}} + \sum_{j=1}^{M}\underbrace{\frac{N_j\bar{a}_j}{N\bar{a}}}_{s_j} \cdot \frac{1}{N_j} \cdot \ln\left(\frac{\bar{a}_j}{\bar{a}}\right)\underbrace{\sum_{i=1}^{N_j}\frac{a_i}{\bar{a}_j}}_{N_j} \\
&= \underbrace{\sum_{j=1}^{M} s_j \cdot T_{a_j}}_{within} + \underbrace{\sum_{j=1}^{M} s_j \cdot \ln\left(\frac{\bar{a}_j}{\bar{a}}\right)}_{between}
\end{aligned}
$$

The product/ratio decomposition

Assume the variable a is the product of b and c, i.e. $a_i = b_i \cdot c_i$. The Theil index for variable a is given by:

$$
\begin{aligned}
T_a &= \frac{1}{N}\sum_{i=1}^{N}\frac{a_i}{\bar{a}}\ln\left(\frac{a_i}{\bar{a}}\right) \quad \text{where} \quad \frac{a_i}{\bar{a}} = \frac{b_i}{\bar{b}} \cdot \frac{c_i}{\bar{c}} \cdot \frac{\bar{b}\bar{c}}{\bar{a}} = \frac{b_i}{\bar{b}} \cdot \frac{c_i}{\bar{c}} \cdot \gamma \text{ ,with } \gamma = 1 - \frac{cov(b,c)}{\bar{a}} \\
&= \frac{1}{N}\sum_{i=1}^{N}\frac{a_i}{\bar{a}}\ln\left(\frac{b_i}{\bar{b}} \cdot \frac{c_i}{\bar{c}} \cdot \gamma\right)
\end{aligned}
$$

$$
\begin{aligned}
&= \frac{1}{N}\sum_{i=1}^{N}\frac{a_i}{\bar{a}}\ln(\frac{b_i}{\bar{b}}) + \frac{1}{N}\sum_{i=1}^{N}\frac{a_i}{\bar{a}}\ln(\frac{c_i}{\bar{c}}) + \ln\gamma\cdot\underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{a_i}{\bar{a}}}_{1} \\
&= \gamma\left[\frac{1}{N}\sum_{i=1}^{N}\frac{c_i}{\bar{c}}\cdot\frac{b_i}{\bar{b}}\ln(\frac{b_i}{\bar{b}}) + \frac{1}{N}\sum_{i=1}^{N}\frac{b_i}{\bar{b}}\cdot\frac{c_i}{\bar{c}}\ln(\frac{c_i}{\bar{c}})\right] + \ln\gamma \\
&= \gamma\Bigg[\underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{b_i}{\bar{b}}\ln(\frac{b_i}{\bar{b}})}_{T_b}\underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{c_i}{\bar{c}}}_{1} + cov(\frac{b_i}{\bar{b}}\ln(\frac{b_i}{\bar{b}}),\frac{c_i}{\bar{c}}) + \\
&\qquad \underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{c_i}{\bar{c}}\ln(\frac{c_i}{\bar{c}})}_{T_c}\underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{b_i}{\bar{b}}}_{1} + cov(\frac{c_i}{\bar{c}}\ln(\frac{c_i}{\bar{c}}),\frac{b_i}{\bar{b}})\Bigg] + \ln\gamma \\
&= \gamma\Big[T_b + T_c\Big] + \underbrace{\left[\ln\gamma + \gamma\left(cov(\frac{b_i}{\bar{b}}\ln(\frac{b_i}{\bar{b}}),\frac{c_i}{\bar{c}}) + cov(\frac{c_i}{\bar{c}}\ln(\frac{c_i}{\bar{c}}),\frac{b_i}{\bar{b}})\right)\right]}_{\Omega} \\
&= \gamma\Big[T_b + T_c\Big] + \Omega
\end{aligned}
$$

Combining between-within and product/ratio decompositions

We assume the variable a pertains to M groups, while being the product of b and c. In our application a is the ratio of interest (VA/INC), while b is value-added per households and c is the inverse of the income per households. In particular, we want to decompose the Theil index for variable a into within and between effects, but also determining the specific contributions of b, c and their interaction (named hereafter $Cov.$). As a picture is worth thousands words, we aim to algebraically fill the matrix below. By using the properties of between-within and product/ratio decompositions, we can already define the borders of the matrix. The column “Total” is found using the between-within decomposition of the a Theil index, while the row “Total” is found using the product/ratio decomposition. We still need to derive algebraically the between and within effects specific to a, b and $Cov.$.

Table B.1: Two-way Matrix decomposition (before completion).

	b	c	$Cov.$	Total
Within	(within)$_b$	(within)$_c$	(within)$_{Cov}$	$\sum_{j=1}^{M} s_j T_{a_j}$
Between	(between)$_b$	(between)$_c$	(between)$_{Cov}$	$\sum_{j=1}^{M} s_j \ln(\frac{\bar{a}_j}{\bar{a}})$
Total	γT_b	γT_c	Ω	T_a

To fill the above matrix, we first need to notice that since $a_i = b_i \cdot c_i$,

$$\bar{a}_j = \sum_{i=1}^{N_j} \frac{a_i}{N_j} = \frac{\bar{b}_j \cdot \bar{c}_j}{\gamma_j} \qquad \text{with} \quad \gamma_j = 1 - \frac{cov(b_j, c_j)}{\bar{a}_j}$$

$$\bar{a} = \sum_{i=1}^{N} \frac{a_i}{N} = \frac{\bar{b} \cdot \bar{c}}{\gamma} \qquad \text{with} \quad \gamma = 1 - \frac{cov(b, c)}{\bar{a}}$$

we have that,

$$\frac{a_i}{a_j} = \frac{b_i c_i}{\bar{b}_j \bar{c}_j}\gamma_j \qquad \text{and} \qquad \frac{\bar{a}_j}{\bar{a}} = \frac{\bar{b}_j \bar{c}_j}{\bar{b}\ \bar{c}} \frac{\gamma}{\gamma_j}$$

Using these and the between-within decomposition shown above, we can write the Theil index of the ratio (T_a) as:

$$\begin{aligned}
T_a &= \sum_{j=1}^{M} s_j \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{b_i c_i}{\bar{b}_j \bar{c}_j}\gamma_j \left[\ln(\frac{b_i c_i}{\bar{b}_j \bar{c}_j}\gamma_j) \right] + \sum_{j=1}^{M} s_j \left[\ln(\frac{b_j c_j}{\bar{b}\ \bar{c}} \frac{\gamma}{\gamma_j}) \right] \\
&= \sum_{j=1}^{M} s_j \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{b_i c_i}{\bar{b}_j \bar{c}_j}\gamma_j \left[\ln(\frac{b_i}{\bar{b}_j}) + \ln(\frac{c_i}{\bar{c}_j}) + \ln(\gamma_j) \right] + \sum_{j=1}^{M} s_j \left[\ln(\frac{b_j}{\bar{b}}) + \ln(\frac{c_j}{\bar{c}}) + \ln(\frac{\gamma}{\gamma_j}) \right] \\
&= \sum_{j=1}^{M} s_j \gamma_j \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{c_i}{\bar{c}_j} \cdot \frac{b_i}{\bar{b}_j} \ln(\frac{b_i}{\bar{b}_j}) + \sum_{j=1}^{M} s_j \gamma_j \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{b_i}{\bar{b}_j} \cdot \frac{c_i}{\bar{c}_j} \ln(\frac{c_i}{\bar{c}_j}) +
\end{aligned}$$

$$\sum_{j=1}^{M} s_j \ln(\gamma_j) \underbrace{\frac{1}{N_j}\sum_{i=1}^{N_j}\frac{a_i}{\bar{a}_j}}_{1} + \sum_{j=1}^{M} s_j \left[\ln(\frac{b_j}{\bar{b}_j}) + \ln(\frac{c_j}{\bar{c}_j}) + \ln(\frac{\gamma}{\gamma_j})\right]$$

$$= \sum_{j=1}^{M} s_j\gamma_j \left[T_{b_j} + cov(\frac{b_i}{\bar{b}}\ln(\frac{b_i}{\bar{b}}), \frac{c_i}{\bar{c}})\right] + \sum_{j=1}^{M} s_j\gamma_j \left[T_{c_j} + cov(\frac{c_i}{\bar{c}}\ln(\frac{c_i}{\bar{c}}), \frac{b_i}{\bar{b}})\right] +$$

$$\sum_{j=1}^{M} s_j \ln(\gamma_j) + \sum_{j=1}^{M} s_j \left[\ln(\frac{b_j}{\bar{b}_j}) + \ln(\frac{c_j}{\bar{c}_j}) + \ln(\frac{\gamma}{\gamma_j})\right]$$

$$= \sum_{j=1}^{M} s_j \left\{\gamma_j\left[T_{b_j} + T_{c_j}\right] + \left[\ln(\gamma_j) + cov(\frac{b_i}{\bar{b}}\ln(\frac{b_i}{\bar{b}}), \frac{c_i}{\bar{c}}) + cov(\frac{c_i}{\bar{c}}\ln(\frac{c_i}{\bar{c}}), \frac{b_i}{\bar{b}})\right]\right\} +$$

$$\sum_{j=1}^{M} s_j \left\{\ln(\frac{b_j}{\bar{b}_j}) + \ln(\frac{c_j}{\bar{c}_j}) + \ln(\frac{\gamma}{\gamma_j})\right\}$$

We want to decompose the respective b and c Theil indices also into within-between effects. To do so, we first need to remember, taking as example variable b, that:

$$T_b = \underbrace{\sum_{j=1}^{M} \frac{N_j \cdot \bar{b}_j}{N \cdot \bar{b}} \cdot T_{b_j}}_{within} + \underbrace{\sum_{j=1}^{M} \frac{N_j \cdot \bar{b}_j}{N \cdot \bar{b}} \cdot \ln(\frac{\bar{b}_j}{\bar{b}})}_{between}$$

We notice that

$$\frac{N_j \cdot \bar{b}_j}{N \cdot \bar{b}} = s_j \frac{\bar{a}}{\bar{a}_j}\frac{\bar{b}_j}{\bar{b}} = s_j \frac{\bar{b}\,\bar{c}}{\bar{b}_j\bar{c}_j}\frac{\bar{b}_j}{\bar{b}}\frac{\gamma_j}{\gamma} = s_j \frac{\bar{c}}{\bar{c}_j}\frac{\gamma_j}{\gamma}$$

Therefore,

$$T_b = \sum_{j=1}^{M} s_j \frac{\bar{c}}{\bar{c}_j}\frac{\gamma_j}{\gamma} \cdot T_{b_j} + \sum_{j=1}^{M} s_j \frac{\bar{c}}{\bar{c}_j}\frac{\gamma_j}{\gamma} \cdot \ln(\frac{\bar{b}_j}{\bar{b}})$$

This implies that the within and between components of T_b (T_c) should be adjusted by a factor $\frac{\bar{c}}{\bar{c}_j}\frac{\gamma_j}{\gamma}$ (respectively $\frac{\bar{b}}{\bar{b}_j}\frac{\gamma_j}{\gamma}$). This also applies in the definition of the overall interaction term, Ω. Therefore, the decomposition rewrites,

$$T_a = \sum_{j=1}^{M} s_j \left\{\frac{\gamma_j}{\gamma}\left[\frac{\bar{c}}{\bar{c}_j}T_{b_j} + \frac{\bar{b}}{\bar{b}_j}T_{c_j}\right] + \left[\ln(\gamma_j) + cov(\frac{b_i}{\bar{b}}\ln(\frac{b_i}{\bar{b}}), \frac{c_i}{\bar{c}}) + cov(\frac{c_i}{\bar{c}}\ln(\frac{c_i}{\bar{c}}), \frac{b_i}{\bar{b}})\right]\right\} +$$

$$\sum_{j=1}^{M} s_j \left\{ \frac{\gamma_j}{\gamma} \frac{\bar{c}}{\bar{c}_j} \ln\left(\frac{b_j}{\bar{b}_j}\right) + \frac{\gamma_j}{\gamma} \frac{\bar{b}}{\bar{b}_j} \ln\left(\frac{c_j}{\bar{c}_j}\right) + \ln\left(\frac{\gamma}{\gamma_j}\right) \right\} +$$
$$\sum_{j=1}^{M} s_j \left\{ \left[1 - \frac{\bar{c}}{\bar{c}_j}\right] \frac{\gamma_j}{\gamma} T_{b_j} + \left[1 - \frac{\bar{b}}{\bar{b}_j}\right] \frac{\gamma_j}{\gamma} T_{c_j} + \left[1 - \frac{\bar{c}}{\bar{c}_j}\right] \frac{\gamma_j}{\gamma} \ln\left(\frac{b_j}{\bar{b}_j}\right) + \left[1 - \frac{\bar{b}}{\bar{b}_j}\right] \frac{\gamma_j}{\gamma} \ln\left(\frac{c_j}{\bar{c}_j}\right) \right\}$$

Hence, we can fill in the table,

Table B.2: Two-way Matrix decomposition (completed).

	b	c	$Cov.$	Total
Within	$\sum_{j=1}^{M} s_j \gamma_j \frac{\bar{c}}{\bar{c}_j} T_{b_j}$	$\sum_{j=1}^{M} s_j \gamma_j \frac{\bar{b}}{\bar{b}_j} T_{c_j}$	$\sum_{j=1}^{M} s_j \Omega_j$	$\sum_{j=1}^{M} s_j T_{a_j}$
Between	$\sum_{j=1}^{M} s_j \frac{\gamma_j}{\gamma} \frac{\bar{c}}{\bar{c}_j} \ln\left(\frac{b_j}{\bar{b}_j}\right)$	$\sum_{j=1}^{M} s_j \frac{\gamma_j}{\gamma} \frac{\bar{b}}{\bar{b}_j} \ln\left(\frac{c_j}{\bar{c}_j}\right)$	$\sum_{j=1}^{M} s_j \Theta_j$	$\sum_{j=1}^{M} s_j \ln\left(\frac{\bar{a}_j}{\bar{a}}\right)$
Total	γT_b	γT_c	Ω	T_a

Where the within and between interaction terms, Ω_j and Θ_j, are given by,

$$\Omega_j = \ln(\gamma_j) + cov\left(\frac{b_i}{\bar{b}} \ln\left(\frac{b_i}{\bar{b}}\right), \frac{c_i}{\bar{c}}\right) + cov\left(\frac{c_i}{\bar{c}} \ln\left(\frac{c_i}{\bar{c}}\right), \frac{b_i}{\bar{b}}\right) + \left[1 - \frac{\bar{c}}{\bar{c}_j}\right] \frac{\gamma_j}{\gamma} T_{b_j} + \left[1 - \frac{\bar{b}}{\bar{b}_j}\right] \frac{\gamma_j}{\gamma} T_{c_j}$$
$$\Theta_j = \ln\left(\frac{\gamma}{\gamma_j}\right) + \left[1 - \frac{\bar{c}}{\bar{c}_j}\right] \frac{\gamma_j}{\gamma} \ln\left(\frac{b_j}{\bar{b}_j}\right) + \left[1 - \frac{\bar{b}}{\bar{b}_j}\right] \frac{\gamma_j}{\gamma} \ln\left(\frac{c_j}{\bar{c}_j}\right)$$

Results

Table B.3: Two-way Matrix decomposition for 2011.

	VPH*	IPH*	Cov.	Total
Within	0.56169	0.01285	-0.02845	0.54609
	(0.01111)	(0.00002)	(0.00285)	(0.01025)
Between	0.04269	0.00860	-0.02146	0.02983
	(0.00306)	(0.00001)	(0.00115)	(0.00272)
Total	0.60438	0.02145	-0.04991	0.57592
	(0.01230)	(0.00003)	(0.00345)	(0.01136)

Notes: * VPH is value-added per household and IPH inverse of income per household.
See Table 1 for the analytical expressions of the decomposition.

Table B.4: Two-way Matrix decomposition for 2012.

	VPH*	IPH*	Cov.	Total
Within	0.55482	0.01249	-0.02801	0.53929
	(0.01090)	(0.00002)	(0.00297)	(0.00901)
Between	0.04783	0.00831	-0.02302	0.03313
	(0.00254)	(0.00001	(0.00124)	(0.00180)
Total	0.60265	0.02080	-0.05103	0.57242
	(0.01145)	(0.00003)	(0.00363)	(0.00922)

Notes: * VPH is value-added per household and IPH inverse of income per household.
See Table 1 for the analytical expressions of the decomposition.

Table B.5: Two-way Matrix decomposition for 2013.

	VPH*	IPH*	Cov.	Total
Within	0.57907	0.01274	-0.03383	0.55797
	(0.01052)	(0.00002)	(0.00322)	(0.00873)
Between	0.04223	0.00812	-0.01904	0.03131
	(0.00287)	(0.00001)	(0.00143)	(0.00217)
Total	0.62129	0.02086	-0.05287	0.58928
	(0.01161)	(0.00003)	(0.00405)	(0.00929)

Notes: * VPH is value-added per household and IPH inverse of income per household.
See Table 1 for the analytical expressions of the decomposition.

Table B.6: Two-way Matrix decomposition for 2014.

	VPH*	IPH*	Cov.	Total
Within	0.60502	0.01239	-0.04264	0.57476
	(0.01159)	(0.00002)	(0.00308)	(0.01189)
Between	0.04557	0.00821	-0.02153	0.03225
	(0.00278)	(0.00001)	(0.00123)	(0.00206)
Total	0.65059	0.02060	-0.06417	0.60702
	(0.01257)	(0.00003)	(0.00384)	(0.01276)

Notes: * VPH is value-added per household and IPH inverse of income per household.
See Table 1 for the analytical expressions of the decomposition.

Appendix C: Spatial analysis of the Production/Income ratio

Figure C.1: Spatial distribution of the ratio VA/INC (value-added over income).

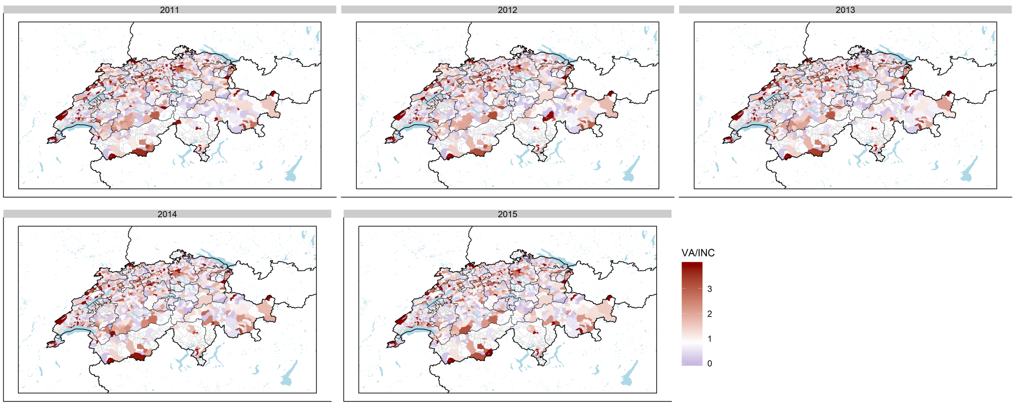


Figure C.2: Spatial distribution of income (INC).

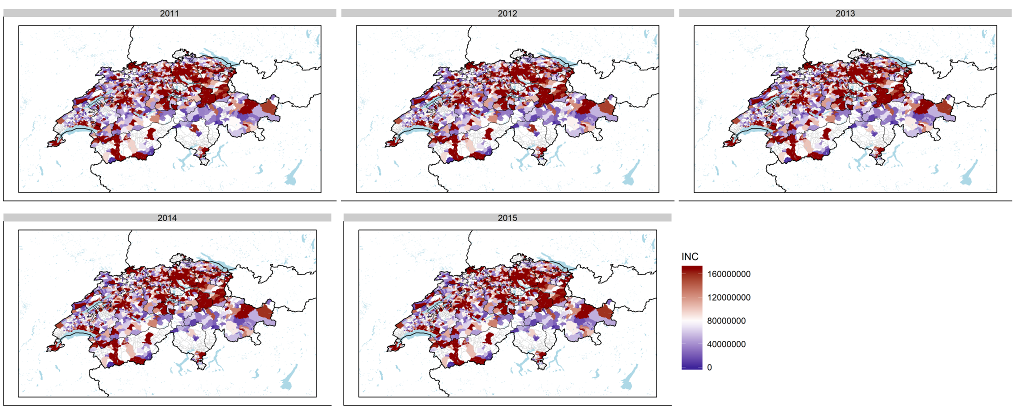


Figure C.3: Spatial distribution of value-added (VA).

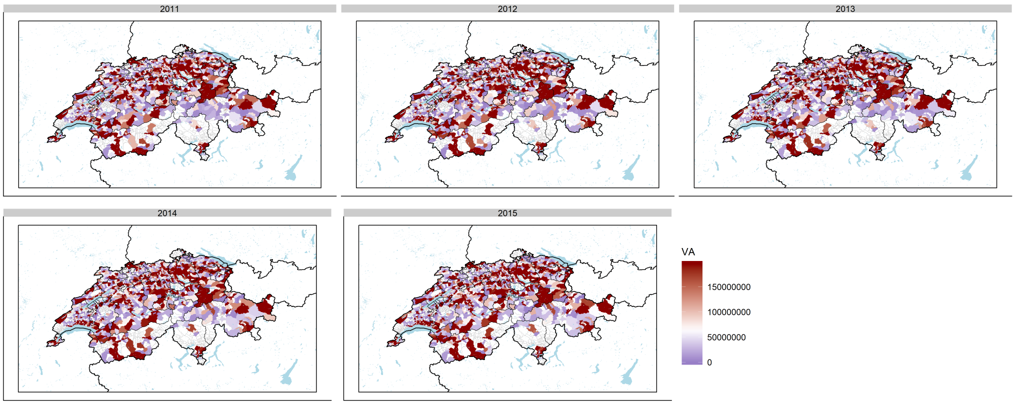
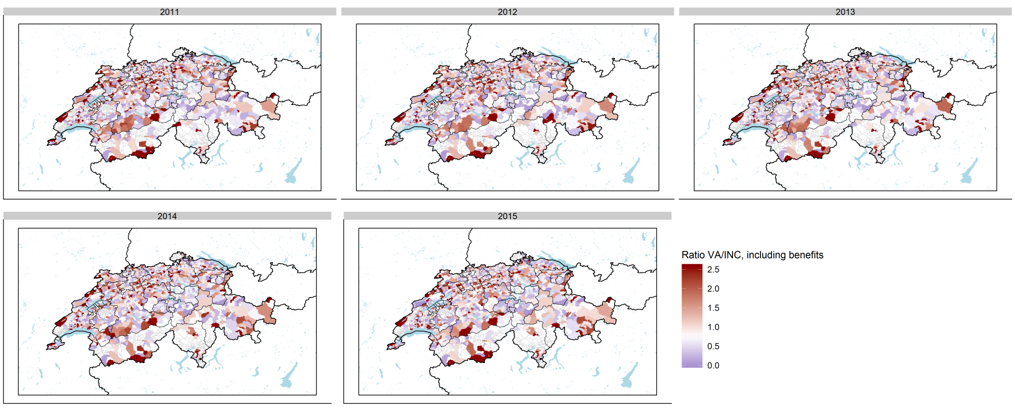


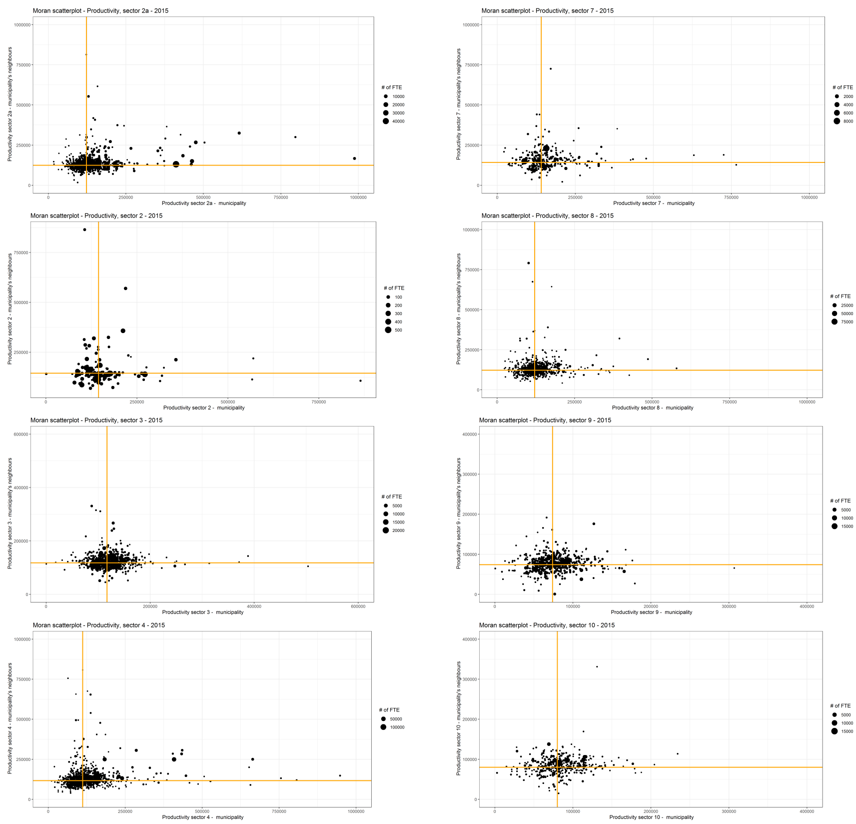
Figure C.4: Spatial distribution of the ratio VA/INC, including benefits.



Moran scatterplots

The following graphs show the value-added per full-time equivalent specific to eight NACE sectors. The value for the municipality itself is represented on the horizontal axis, while the vertical dimension represents the average among its contiguous municipalities (that are available in the dataset, for this sector).

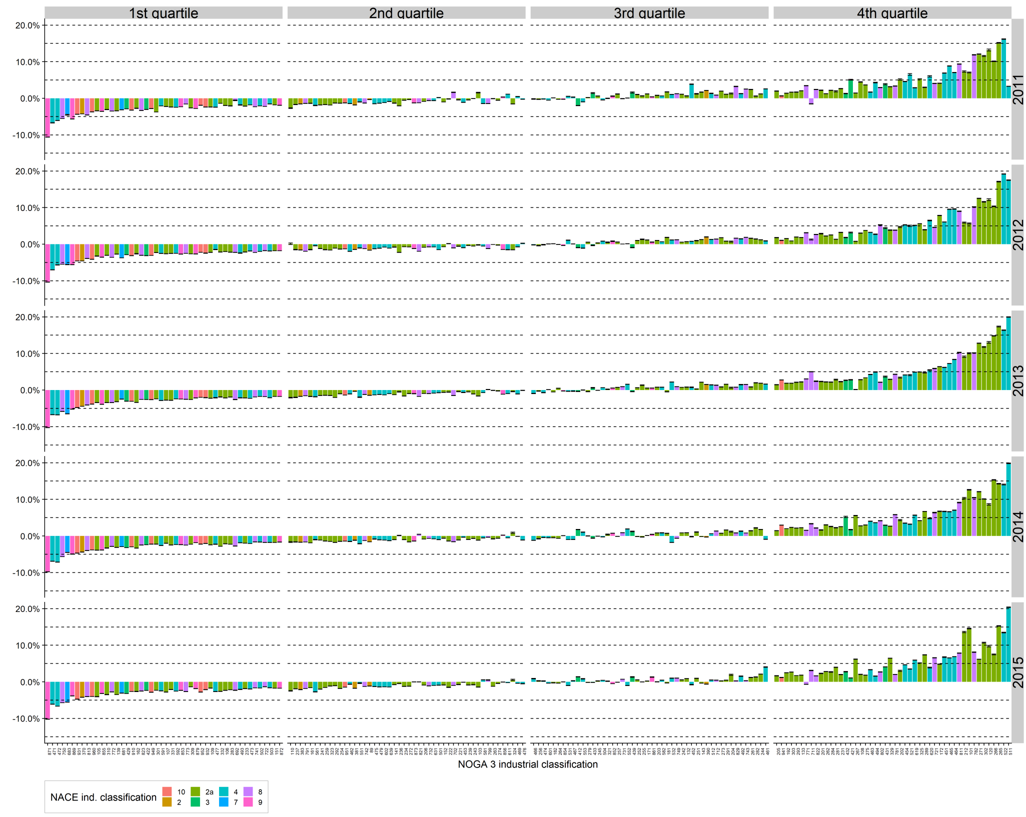
Figure C.5: Moran Scatterplots per industry.



Sector 2a: manufacturing industries; sector 2: extraction and other industries; sector 3: building sector; sector 4: whole/retail sales, transports, hotels/restaurant, TIC; sector 7: real estate; sector 8: scientific/ technical activities, administrative services; sector 9: public administration, defense, teaching, health and social activities; sector 10: other services.

Appendix D: Industries Correlogram

Figure D.1: Correlation between share of employment active per industry and ratio VA/INC.



Note: correlations are computed on each of the 400 datasets, averages are presented along with the means 95% confidence intervals. The correlations are ordered based on their yearly average value. Quartiles are computed on yearly averages as well.

The high correlation in the manufacturing sector is driven mainly by four sectors: the tobacco-based production (120), the pharmaceutical production (212), the manufacturing of medical irradiation and electromagnetic devices (266) and production of watches and precision measurement instruments (265). This explains the high ratios observed in la Vallée de Joux and le Locle, whose economy is based on the watch industry, Neuchâtel, whose economy is fuelled by the watch and tobacco-based production and Basel, turned towards the pharmaceutical industry. When looking at the other extreme, the most negative correlation was found in the health sector (NACE 9). This correlation is driven by the care-home residence sector (871). Such services should localize on the entire territory and not only in dense urban area or near related-industries. Therefore it does not benefit neither from urbanization nor localization economies. In the other industrial sections, we note other several interesting cases at a more disaggregated level. The wholesale sector (463 to 469) exhibits high correlation with the ratio, all being in the last distribution quartile, especially wholesale of domestic goods (464) (pharmaceutical products included). As shown in Chapter 3, this type of activities benefit mainly from urbanization economies. Industries cluster together in dense urban areas which therefore have high value-added. Another important positive correlations can be found in the sector of aerial transportation (511) (and related services (522)), in placement agencies (781, 782) or house-cleaning service (811) for a similar reason. In other words, these industries locate in cities and, therefore, correlate with the large wealth created in urban center.

We identify also industries negatively correlated with the ratio of interest. The cases of retail business (471, 472) and restaurants (561) are similar to the one of home-care residence. They have a negative correlation because their consumption is locally determined and therefore spread over all the territory.

General Conclusion

1 Main Findings

This thesis explores empirically the Swiss economic landscape from three complementary perspectives. It describes productivity patterns on the basis of novel and firm-level value-added databases. It estimates agglomeration economies. It investigates the spatial mismatch between production and income. These three approaches provide a comprehensive view about regional competitiveness in Switzerland. The main findings are summarized below, followed by a brief discussion on policy implications (cf. section 2) and limitations (cf. section 3).

The first contribution of the thesis is the construction of novel value-added databases for Switzerland for the period 2011-2015, presented in Chapter 1. The results are broadly in line with the aggregated value-added figures estimated by the FSO. In Chapter 2, these firm-level data are used to capture productivity growth patterns. It appears that the Swiss low productivity puzzle hides a large heterogeneity across regions and industries, with a particularly weak performance of the Mittelland and the Real estate sector. Overall, productivity differences tend to be larger across geographical units than across sectors. The results also show that incrementing the number of geographical units and/or industrial categories increases the magnitude of structural effects, while competitive effects dominate at the highest level of aggregation. This confirms that the availability of disaggregated data is key in capturing the impact of regional specialisation.

Chapter 3 uses a two-step procedure which allows to quantify and disentangle agglomeration economies. The results validate, in the Swiss context, two major findings of the literature. First, both types of agglomeration economies matter and are negatively related. Second, industries characterized by a high degree of specificity, whether in terms of specialized inputs or particular skills of the labor force, tend to co-locate in similar areas generating localization economies. On the contrary, broad-based industries, flourishing in large urban centers, suffer from being located in highly specialized regions. These two results are robust across specifications.

Finally, in Chapter 4, we challenge the conventional wisdom of what makes a municipality rich (or poor). We establish four main findings. First, the empirical results are in line with the equilibrium outcomes suggested by NEG models. Second, Theil decompositions show that spatial differentiation takes place at the municipal –rather than the cantonal– level. Third, value-added (per household) inequalities are larger than income ones, pointing towards stronger agglomeration forces on the firms' side than on the households' side. Finally, municipalities with the highest value-added to income ratios are the ones benefiting from agglomeration economies, while the low-ratio municipalities are organized as "surrounding belts" located nearby productive centers.

2 Policy Implications

Despite the general limitations exposed in section 3, the above-mentioned results suggest a number of policy implications.

As the aggregate Swiss low productivity performance is not a common feature shared by all firms, across-the board policies to boost productivity growth may not be particularly appropriate in Switzerland. A particular care should be devoted to identify the specific reasons of the laggards, and targeted measures are likely to be the most effective ones.

Although the results of Chapter 3 are still vague regarding the exact mechanisms underlying agglomeration economies, two recommendations emerge. First, spatial development policies should aim at improving the local environment for mature industries with large localization effects. Second, innovation policies, whose concern is to develop and support small innovative firms, which are crucial for the Swiss economy, should be introduced and supported in large urban centers.

Finally, Chapter 4 suggests policy implications in two areas. On the one hand, regarding infrastructure development, one should keep in mind that the spatial mismatch between production and income would be reinforced by a decrease in commuting costs, which in turn, would increase the need for commuting and, consequently, the related external costs. From a policy perspective, it means that infrastructure investments should prioritize projects where the private to social marginal cost gap of commuting is low, in order to minimize externalities.

On the other hand, even if fiscal federalism probably contributes to lower spatial inequalities in income, fiscal competition and regional equity cannot be ignored. The high degree of spatial specialization of Swiss municipalities is reinforced by the current fiscal system, as rich municipalities can afford to set lower tax rates, attracting rich households and/or more firms. This points towards a potential redefinition of what makes a region contribute or benefit from federal transfers, including the location of production as an additional parameter in the fiscal equalization debate.

3 General limitations and further research

One of the major limitations of the thesis lies in the assumptions made in the construction of the value-added databases detailed in Chapter 1. The *restricted* sample is small and clearly biased towards large firms, which weakens its representativity. The *naive* imputed sample is more representative but relies on specific proportionality rules, rendering this dataset improper for productivity analyses over time. The *multiple imputation* databases are probably the best balance between assumptions, time construction efficiency and number of observations. However, their values come along with uncertainty around the estimates. In addition, in spite of our efforts to construct representative weights, there is nothing we can do in the (rare) cases where a specific industry is totally absent from the sample. These caveats illustrate the challenges of collecting appropriate value-added data in Switzerland, and the necessity to pursue efforts in promoting both data accessibility and firms' survey participation.

While the methodology used in Chapter 2 allows for a clear identification of productivity patterns, competitive and structural effects, and provides precious insights about the Swiss low productivity puzzle, it remains a descriptive approach. Further investigations are needed to explore the determinants of regional productivity patterns, including in particular neighbouring effects and international exposure.

A similar criticism is warranted for the estimates of agglomeration economies provided by Chapter 3. Much remains to be done to understand the precise mechanisms that are at work behind the identified localization and urbanization effects, in particular on the labor and input markets. Adding more control variables would help in rising the overall explanatory power of the model and in articulating more rigorous policy recommendations.

In Chapter 4, this thesis argues for the inclusion of production in the fiscal equalization debate and for more equity across regions. However, it falls short of defining and comparing a set of alternatives to the present system. These issues certainly deserve future research efforts.

Finally, while describing the various forces that shape the spatial specialization of the Swiss landscape, the present study does not fully address the consequences of these agglomeration forces, especially in terms of infrastructure development and environmental impact. A deeper knowledge of these forces is required to better understand, and possibly simulate, the development of Swiss cities and regions in the future.

Bibliography

Administration Fédérale des Contributions, 2013. Introduction aux chiffres-clés de l'impôt fédéral direct. Département fédéral des finances (DFF).

Allen, T., Arkolakis, C., 2014. Trade and the topography of the spatial economy. Quaterly Journal of Economics 129, 1085–1140.

Arvanitis, S., Ley, M., Seliger, F., Stucki, T., Wörter, M., 2013. Innovationsaktivitäten in der schweizer Wirtschaft: eine Analyse der Ergebnisse der Innovationserhebung 2011. Technical Report. KOF Studien.

Ashby, L.D., 1964. The geographical redistribution of employment: An examination of the elements of change. Survey of Current Business 44, 13–20.

Axhausen, K.W., Bischof, T., Neuenschwander, R., Sarlas, G., Walker, P., 2015. Gesamtwirtschaftliche Effekte des öffentlichen Verkehrs mit besonderer Berücksichtigung der Verdichtung- und Agglomerationseffekte: Schlussbericht. Arbeitsberichte Verkehrs-und Raumplanung 1079.

Bacher, H.U., Brühlart, M., 2013. Progressive taxes and firm births. International Tax and Public Finance 20, 129–168.

Baldwin, R., Forslid, R., Martin, P., Ottaviano, G., Robert-Nicoud, F., 2005. Economic geography and public policy. Princeton University Press.

Barff, R.A., Knight, P.L., 1988. Dynamic shift-share analysis. Growth and Change 19, 1–10.

Behrens, K., Duranton, G., Robert-Nicoud, F., 2014. Productive cities: sorting, selection, and agglomeration. Journal of Political Economy 122, 507–553.

Bolli, T., Farsi, M., 2015. The dynamics of productivity in Swiss universities. Journal of Productivity Analysis 44, 21–38.

Borck, R., Pflüger, M., Wrede, M., 2009. A simple theory of industry location and residence choice. Journal of Economic Geography 10, 913–940.

Brühlart, M., Schmidheiny, K., 2011. On the equivalence of location choice models: Conditional Logit, nested Logit and Poisson. Journal of Urban Economics 69, 214–222.

Brühlart, M., Schmidheiny, K., 2015. On nesting location choice model correctly: A reply to Herger and McCorriston (Economics Letters, 2013) .

Brülhart, M., Jametti, M., Schmidheiny, K., 2012. Do agglomeration economies reduce the sensivity of firm location to tax differentials? The Economic Journal 122, 1069–1093.

Brueckner, J.K., Thisse, J.F., Zenou, Y., 1999. Why is central Paris rich and downtown Detroit poor?: An amenity-based theory. European Economic Review 43, 91–107.

Brunetti, A., Zurcher, B., 2002. Das tiefe Wachstum der Schweizer Arbeitsproduktivität. SECO Working Paper 4.

Caliendo, M., Parro, F., Rossi-Hansberg, E., 2017. The impact of regional and sectoral productivity changes on the US economy. The Review of Economic Studies 85, 2042–2096.

Carlton, D.W., 1983. The location and employment choices of new firms: An econometric model with discrete and continuous endogenous variables. The Review of Economics and Statistics 65, 440–449.

Chang, H.H., van Marrewijk, C., Schramm, M., 2015. Handbook of Research Methods and Applications in Economic Geography. Edward Elgar Publishing. chapter 19: Empirical studies in geographical economics. p. 391.

Combes, P.P., Gobillon, L., 2015. Handbook of Regional and Urban Economics. Elsevier. volume 5. chapter 5: The empirics of agglomeration economies. pp. 247–348.

Crozet, M., 2004. Do migrants follow market potentials? An estimation of a New Economic Geography model. Journal of Economic Geography 4, 439–458.

Dunn, E.S., 1960. A statistical and analytical technique for regional analysis. Papers in Regional Science 6, 97–112.

Duranton, G., Puga, D., 2001. Nursery cities: Urban diversity, process innovation, and the life cycle of products. American Economic Review 91, 1454–1477.

Eaton, J., Kortum, S., 2002. Technology, geography and trade. Econometrica 70, 1741–1779.

Ecoplan, 2017. Charges de centre des villes - rapport de synthèse. Conférence des directrices et directeurs des finances des villes (CDFV).

Erkus-Ozturk, H., Terhorst, P., 2018. Economic diversification of a single-asset tourism city: Evidence from Antalya. Current Issues in Tourism 21, 422–439.

Esteban-Marquillas, J.M., 1972. Shift- and share analysis revisited. Regional and Urban Economics 2, 249–261.

Federal Statistical Office, 2016. Produit intérieur brut par grande région et par canton. Rapport méthodologique.

Fuchs, V., 1962. Statistical explanation of the relative shift of manufacturing among regions of the United States. Papers in Regional Science 8, 105–126.

Fujita, M., Krugman, P., Venables, A.J., 1999. The Spatial Economy: Cities, Regions and International Trade. MIT Press.

Fujita, M., Thisse, J.F., 2002. Economics of Agglomeration: Cities, Industrial Location and Regional Growth. Cambridge University Press.

Gallo, J., Ertur, C., 2003. Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980–1995. Papers in Regional Science 82, 175–201.

Geary, F., Stark, T., 2016. What happened to regional inequality in Britain in the twentieth century? The Economic History Review 69, 215–228.

Graham, D.J., 2009. Identifying urbanisation and localisation externalities in manufacturing and service industries. Papers in Regional Science 88, 63–84.

Graham, J.W., Olchowski, A.E., Gilreath, T., 2007. How many imputations are really needed? Some practical clarifications of multiple imputation theory. Prevention Science 8, 206–213.

Grass, M., Fry, S., Vaterlaus, S., 2017. The importance of the pharmaceutical industry for Switzerland. Interpharma, Basel.

Greenstone, M., Hornbeck, R., Moretti, E., 2010. Identifying agglomeration spillovers. Evidence from winners and losers of large plant openings. Journal of Political Economy 118, 536–598.

de Groot, H.L., Poot, J., Smit, M., 2016. Which agglomeration externalities matter most and why? Journal of Economic Surveys 30, 756–782.

Guimarães, P., Figueiredo, O., Woodward, D., 2003. A tractable approach to the firm location decision problem. Review of Economics and Statistics 85, 201–204.

Hashiguchi, Y., Tanaka, K., 2015. Agglomeration and firm-level productivity: A Bayesian spatial approach. Papers in Regional Science 94, 95–114.

Helpman, E., 1998. The size of regions. Topics in public economics: Theoretical and applied analysis, 33–54.

Holl, A., 2004. Transport infrastructure, agglomeration economies and firm birth: Empirical evidence from Portugal. Journal of Regional Science 44, 693–712.

Jofre-Monseny, J., Marín-López, R., Viladecans-Marsal, E., 2014. The determinants of localization and urbanization economies: Evidence from the location of new firms in Spain. Journal of Regional Science 54, 313–337.

Kaiser, B., Siegenthaler, M., 2015. The productivity deficit of the knowledge-intensive business service industries in Switzerland. SECO Strukturberichterstattung 54/3.

Kohli, U., 2005. Diagnose: Wachstumsschwäche. Die Debatte über die Fehlende Dynamik der Schweizerischen Volkswirtschaft. Neue Zürcher Zeitung. chapter Switzerland's growth deficit: A real problem—but only half as bad as it looks.

Krugman, P., 1991. Increasing returns and economic geography. Journal of Political Economy 99, 483–499.

Lee, S., Lin, J., 2017. Natural amenities, neighbourhood dynamics, and persistence in the spatial distribution of income. The Review of Economic Studies 85, 663–694.

Leuba, J., 2019. Natural amenities and the spatial distribution of Swiss income. IRENE - Université de Neuchâtel.

Lewrick, U., Weder, L., Weder, R., 2018. Productivity growth from an international trade perspective. Review of International Economics 26, 339–356.

López-Bazo, E., Vayá, E., Artis, M., 2004. Regional externalities and growth: Evidence from European regions. Journal of regional science 44, 43–73.

Marshall, A., 1920. Principles of Economics. Macmillan, London.

Marti, M., Peter, C., Setz, M., Matter, D., Schönbächler, R., 2017. Regionale Analyse der Arbeitsproduktivität. SECO Strukturberichterestattung 54/6.

Martin, P., 2009. The geography of inequalities in Europe. Spatial Disparities and Development Policy, Washington, DC: The World Bank, 239–256.

Mattmann, M., Walter, F., Meuli, N., 2016. Statistische Grundlagen zu Neugründungen und Wachstumsstarken Unternehmen. Staatssekretariat für Wirtschaft SECO, Direktion für Standortförderung.

Mayor, M., López, A.J., 2005. The spatial shift-share analysis new developments and some findings for the spanish case. Proceedings of the European Regional Science Association, ESRA.

Mayor, M., López, A.J., 2007. Spatial shift-share analysis versus spatial filtering: An application to Spanish employment data. Empirical Economics 34, 123–142.

Mazek, W.F., Chang, J., 1972. The chicken or egg fowl-up in migration: Comment. Southern Economic Journal, 133–139.

McFadden, D., 1974. Frontiers in Econometrics. Academic Press, New York. chapter 4 : Conditional Logit analysis of qualitative choice behavior.

Milanovic, B., 1999. True World Income Distribution, 1988 and 1993: First Calculations, Based on Household Surveys Alone. The World Bank.

Muth, R.F., 1971. Migration: chicken or egg? Southern Economic Journal, 295–306.

Nazara, S., Hewings, G.J., 2004. Spatial structure and taxonomy of decomposition in shift-share analysis. Growth and Change 35, 476–490.

Oates, W.E., 1969. The effects of property taxes and local public spending on property values: An empirical study of tax capitalization and the Tiebout hypothesis. Journal of political economy 77, 957–971.

OECD, 2017. OECD Economic Surveys: Switzerland.

Oguz, S., Knight, J., 2010. Regional economic indicators: With a focus on sub-regional gross value added using shift-share analysis. Economic and Labour Market Review 4, 74–87.

Ollivaud, P., 2017. Boosting productivity in Switzerland. OECD Economics Department Working Papers 1443.

Otsuka, A., 2016. Regional energy demand in Japan: Dynamic shift-share analysis. Energy, Sustainability and Society 6.

Renski, H., 2011. External economies of localization, urbanization and indutrial diversity and new firm survival. Papers in Regional Science 90.

Rodríguez-Pose, A., Hardy, D., 2016. Firm competitiveness and regional disparities in Georgia. Geographical Review 107, 384–411.

Rosenthal, S.S., Strange, W.C., 2004. Handbook of Urban and Regional Economics. chapter 49: Evidence on the nature and sources of agglomeration economies. pp. 2119–2171.

Rubin, D.B., 1987. Multiple Imputation for Nonresponse in Surveys. John Wiley and Sons, Inc.

SAS Institute Inc., 2015. SAS/STAT 14.1 User's Guide. Cary, NC: SAS Institute Inc.. chapter 75: The MI Procedure.

Schafer, J.L., Graham, J.W., 2002. Missing data: Our view of the state of the art. Psychological Methods 7, 147–177.

Schaltegger, C.A., Somogyi, F., Sturm, J.E., 2011. Tax competition and income sorting: Evidence from the Zurich metropolitan area. European Journal of Political Economy 27, 455 – 470.

Schmidheiny, K., 2006. Income segregation and local progressive taxation: Empirical evidence from Switzerland. Journal of Public Economics 90, 429 – 458.

Selting, A.C., Loveridge, S., 1994. Testing dynamic shift-share. Journal of Regional Analysis and Policy 24.

Siegenthaler, M., 2015. Has Switzerland really been marked by low productivity growth? Hours worked and labor productivity in Switzerland in a long-run perspective. Review of Income and Wealth 6, 353–372.

Siegenthaler, M., Stucki, T., 2015. Dividing the pie: The determinants of labor's share of income on the firm level. ILR Review 68, 1157–1194.

Stadelmann, D., Billon, S., 2012. Capitalisation of fiscal variables and land scarcity. Urban Studies 49, 1571–1594.

Stiglitz, J., Sen, A.K., Fitoussi, J.P., 2007. Report by the Commission on the Measurement of Economic Performance and Social Progress.

Stohr, C., 2014. Growth poles: agglomeration economies and economic growth in switzerland from 1860 to 2008. UNIGE Working Paper Series 14-09-2.

Tiebout, C.M., 1956. A pure theory of local expenditures. The journal of political economy 64, 416–424.

Tille, C., 2018. Blog of Cédric Tille, The worrying stagnation of Swiss productivity. `https://blogs.letemps.ch/cedric-tille/2018/01/11/the-worrying-stagnation-of-swiss-productivity/`. [Online; accessed 29-July-2019].

Tissot-Daguette, B., 2019. Measuring agglomeration economies in Switzerland. IRENE - Université de Neuchâtel.

Tissot-Daguette, B., Grether, J.M., 2019. Multiple imputation techniques: An application to Swiss value-added data. IRENE - Université de Neuchâtel.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press.

Yuan, Y., 1994. Multiple imputation using SAS software. Journal of Statistical Software 45.