Technological Innovations and Labor Demand Using Linked Firm-Level Data

Cross-country analyses of technological innovations and labor demand based on harmonized, multi-linked and micro-aggregated firm-level data

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Cross-country analyses of technological innovations and labor demand based on harmonized, multi-linked and micro-aggregated firm-level data

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Abstract

This chapter illustrates how the relationship between technological innovations and labor demand can be analyzed in a cross-country setting by use of harmonized, multi-linked and micro-aggregated firm-level data. An investigation of the relationship between new market product (market novelty) sales and labor demand (employment) derived from a two-output cost function is used as an example. The example is embedded in recent literature and discussions on data availability, data limitations and possible estimation methods. Fixed effects estimations reveal that the sales of market novelties has a significant impact on relative employment in the representative manufacturing firm. In contrast, employment in the representative service firm does not benefit from new market products but rather from the intensity with which information and communication technology innovations are used (in this case the proportion of broadband internet connected employees). The results coincide with those in the firm-level literature, but the approach allows inclusion of a broader variety of firm characteristics, such as firm size, international experience and ICT intensity.

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Introduction

Since the development of the OSLO manual in 1992 (OECD/European Commission, 2018) and the subsequent and systematic collection of innovation data across the world, there are now numerous firm-level studies on the impact of product and process innovations on labor demand (Mairesse and Mohnen, 2010, Ugur, Awaworyi Churchill, and Solomon, 2018). Research earlier than these primarily concern the sectoral level, where information about R&D ventures or patent applications are used as measures of innovation activities (Bogliacino and Vivarelli, 2012). More recently, opportunities to analyze firm behavior based on linked data have improved, although mainly within the boundaries of research on single countries. Multi-linked firm-level data (production, ICT, innovation and business statistics, for instance) allows broader analyses and possibly better measures of different phenomenon, but unfortunately introduce issues of panel attrition and selection bias.

In the wake of new data there are also methodological developments, such as the structural approach by Harrison, Jaumandreu, Mairesse and Peters (2008) and the increasing use of quantile regression and dynamic panel data models (Calvino, 2018; Falk, 2015; Lachenmaier and Rottmann, 2011; Meschi, Tyamz and Vivarelli, 2016). However, studies using multi-linked comparable firm-level data on innovation activities for a number of countries with similar specifications and methods are still rare.

The aim of this chapter is to demonstrate the benefit of analyzing the relationship between labor demand and innovations (products and processes) by use of micro-aggregated, harmonized, and multi-linked firm-level data for the representative firm in nine European countries. Such data is more easily accessible and allow advanced econometrics, alternative measures and comparability across countries. Likewise, a rich dataset facilitates the derivation of labor demand from a CES cost function. The example is embedded in recent literature and discussions on data availability, data limitations and possible estimation methods.

The link between technological innovations and labour demand is extensively analysed (see Pianta, 2005, Calvino and Virgillito, 2018; Vivarelli, 2014 for reviews of the literature and Ugur et al., 2018 for a meta-analysis). There is also a growing literature on the impact of digitalization and automation on labor demand (see Biagi and Falk, 2017; Pantea, Sabadash and Biagi, 2017), where process innovations are often linked to ICT. However, broader literature on this is not taken into account in this chapter, even though the estimations include a variable controlling for employee broadband connectivity, nor are intangible assets other than R&D expenditures considered. In addition, technological innovations other than products and processes, environmental, for instance (Horbach and Rennings, 2013), are also not considered in this context. Finally, heterogeneous labor demand is excluded, although it is evident from the literature that technologies are skilled and task-based (Goos, Manning and Salomons, 2009, 2014). The reason for this is simply a lack of data that would reduce the example to a small group of countries.

Theoretical background

Generally, technological innovations may appear either in the guise of new products or processes. According to the Oslo manual, process innovations include *new or improved production methods; logistics, delivery and distribution systems as well as back office activities, such as maintenance, purchasing, and accounting operations* (OECD/European Commission, 2018). *Significant changes in specific techniques, equipment or software* may also be identified as process innovations. These innovations are expected to reduce the cost of production and thus make it more efficient (Vivarelli, 2014). Improved processes may lead to a reduction in employment as well as in intermediate materials. The possible direct negative impact of process innovation on employment is commonly referred to as the *displacement effect* (see for instance Harrison, Jaumandreu, Mairesse and Peters, 2008, 2014 for a comprehensive description). There is also a likelihood of indirect influences on employment. Process innovations that increase efficiency and productivity can stimulate product demand via lower prices and thus generate demand for labor, referred to as the *compensation effect* (Harrison et al., 2008, 2014). The size of the compensation effect depends on the elasticity of demand for the products as well as on competition from other firms (Harrison et al., 2008, 2014). Thus, the total impact of process innovation on employment depends on which of the two mechanisms dominates.

The Oslo manual suggests two definitions of product innovations, one broad formulated as *the market introduction of a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems* and one narrow defined as *new or significantly improved products that are introduced onto the market before the competitors* (OECD/European Commission, 2018). According to the broader definition an original or improved product innovation must be new to the firm but not necessarily to the market. The narrow definition means the opposite, that the product has to be new to the market (that is, introduced ahead of the competitors).

Just like with new processes, the relationship between labor demand and original products can affect employment directly as well as indirectly. Introduction of new products directly stimulates market expansion and hence employment. However, the market expansion of innovating firms may lead to a displacement of less competitive firms (business stealing effect). At the aggregate level the net effects are unclear (Vivarelli, 2014).

There are several ways to derive the labor demand equation. One alternative is the structural model suggested by Harrison et al. (2008, 2014), which differentiates the manufacturing efficiency of old and new products. Another is to base the equation on a multi-output cost function with two types of outputs: turnover from new (market novelties) or existing products (Falk and Hagsten, 2018). A third approach commonly used is to specify a standard labor demand equation where employment is a function of wages, output and dummy variables approximating product and process innovations (Bond and Van Reenen, 2007; Van Reenen, 1997). Not seldom are the empirical specifications driven by data deficits (disclosure, selection bias, attrition) rather than by the research question itself.

Innovation data sources

There are several representative sources available for information on product and process innovations in firms, some major (see Table 1). Among them are statistics based on official innovation surveys, in Europe labelled the Community Innovation Survey (CIS). This survey is conducted by each EU member state (and in affiliated countries) since the beginning of the 1990s, duly coordinated by Eurostat (Mairesse and Mohnen, 2010; data source a, Table 1 and in References). CIS-type surveys are also available and analyzed in other parts of the world (Crespi, Tacsir and Pereira, 2019; Hou et. al., 2018; Lim and Lee, 2019). Several indicators are available for product innovations: i) dummy variable if the firm introduces new products (market novelties), ii) proportion of turnover related to products new to the firm and iii) proportion of turnover related to products new to the market (novelties). Process innovations are only illustrated by dummy variables. In addition to this, information on innovation expenditures and if firms conduct R&D activities can be found. The CIS is the most comprehensive data source on innovation activities with its three continuous variables on product innovations and innovation inputs.

Table 1: Overview of representative innovation datasets

	Measure of innovation activity											
	Pro-duct	New to market	Process	New to firm	New to market	R&D		Sampling	Coverage			
	Y/N	Y/N	Y/N	Per cent of turnover		Y/N	Amount	design	Country	Sector	Size	Years
OSLO manual (e.g. CIS)[a]	X	X	X	X	X	X		Rotating cross-section	World-wide, EU	Man, services	>10	1992-
BEEPS[b]	X	X	X	X				Rotating cross-section	Emerging and developing	Man, services	>5	2002-
EFIGE[c]	X	X	X	X		X		Cross-section	7 EU	Man	>10	2007-2009
ESEE[d]	X		X			X	X	Panel	ES	Man	>10	1990-
JRC-IPTS[e]							X	Panel	EU	Man, services	Large firms	1990-
UK Small Business[f]	X	X	X	X			X	Panel	UK	Man, services	1-249	2007-
IAB establishment panel[g]	X	X				X		Panel	DE	Man, services	1-	1993-

Notes: Firm size is measured as number of employees and *Man* is short for manufacturing. Y/N means Yes/No.
Source: See reference list.

Beside the CIS, several other surveys follow the OSLO manual in the identification of product and process innovations, like the World Bank Enterprise Survey, the First survey on European Firms in a Global Economy (EFIGE), ESEE (Encuesta Sobre Estrategias Empresariales), the UK Small Business Survey and the German IAB establishment panel. All these surveys use a sampling design where firms are stratified by industry, size, and location, thus leading to representativeness of the universe in a given sector, size-class or year. Some innovation surveys are limited to firms with ten employees or more. Exceptions to this are the BEEPS (World Bank), the IAB establishment survey (Ellguth, Kohaut and Möller, 2014) and the UK Small Business Survey with thresholds of one and five employees.

There are also variations in the country coverage or country participation across surveys. The innovation and the World Bank Enterprise Survey are conducted worldwide with the latter limited to emerging and developing countries, although they are not accessible jointly from one database or necessarily linkable over time. These surveys, implemented in European and Central Asian countries are also known as the Business Environment and Enterprise Performance Surveys (BEEPS) and are jointly undertaken by the World Bank Group, the European Bank for Reconstruction and Development (EBRD), the European Investment Bank (EIB) and the European Commission (EC) (data source b). A major difference between the CIS and the World Bank enterprise survey is that the latter lack questions about turnover from market novelties. Recent applications include Avenyo, Konte and Mohnen (2019) as well as Cirera and Sabetti (2019).

The majority of innovation surveys covers both manufacturing and service firms, except the EFIGE and the ESEE, who are limited to the former. The ESEE survey is funded by the Spanish Ministry of Industry and is an example of a dataset where firm-level information on balance-sheets is linked to data on strategies and innovation activities (data source d). A clear advantage of the dataset is the considerable overlap over time, as opposed to the CIS, which suffers from a high level of attrition because of the rotating design created to ease the response burden of firms. At the Eurostat Safe Centre, the firm-level innovation data is anonymized, implying that they cannot be linked over time, which is possible to do at their national storages. Thus, one feature that distinguishes ESEE from other innovation statistics is the build-up as a panel, which requires systematic tracking of changes in the legal status and industry affiliation of the firm. This dataset is extensively used in the literature for analyses on the relationship between technological innovations and employment (see Bianchini and Pellegrino, 2019; Calvino, 2018; Ciriaci, Moncada-Paternò-Castello and Voigt, 2016; Giuliodori and Stucchi, 2012; Pellegrino, Piva and Vivarelli, 2019; Triguero, Córcoles and Cuerva, 2014 for recent examples).

The IAB Establishment Panel is a large and representative firm-level survey, linkable over time, of all German industries with around 16,000 observations per year (data source g). Information includes new-to-firm and new-to-market products as well as process innovations. In addition, there is information on R&D activities and employees.

The UK Longitudinal Small Business Survey (LSBS) covers around 15,500 firms per year and contains information on the drivers of business performance (data source f). Data on technological innovations are limited to process and product innovations (new market products and other products).

The R&D survey (linked with balance sheet data) initiated by the JRC-IPTS is another example of a firm-level panel set with information on innovation activities. However, information on these activities is limited to R&D expenditures for approximately 2,500 large firms based on information disclosed in annual reports and financial statements. This means that firms that do not provide figures for R&D investments are excluded from the scoreboard (data source e).

The EFIGE database, encompassing a representative selection of firms in seven European countries, partly mirrors information extracted from the CIS, although service firms are excluded and there is no data on turnover from market novelties (data source c and Altomonte and Aquilante, 2012). The dataset is increasingly used for research on the impact of innovation activities, but the cross-sectional design does not allow panel data methods.

There are several other single country datasets, not elaborated on here because they only contain information on R&D expenditures, for instance the Capitalia-Mediocredito Centrale Survey for Italy (Di Cintio, Gosh and Grassi, 2017) or information on different types of investments such as the KFW SME Panel (Baumann and Kritikos, 2016) in a non-harmonized way.

Common estimation methods

As mentioned in the theoretical section, empirical derivation of labor demand might be affected by data availability. This fact applies also to the estimation methods in general, of which there is a variety. Studies based on cross-sectional firm-level data most often use OLS, robust regression or quantile regressions (Calvino, 2018; Dachs and Peters, 2014; Falk, 2015, for instance). Panel datasets allow dynamic modelling where time-invariant fixed effects, persistence of employment and lagged effects of technological innovations can be taken into account (Bogliacino, Piva and Vivarelli, 2012; Meschi, et al., 2016), by the commonly used System GMM estimator, for instance. An important estimation problem is that the decision to introduce product or process innovations is likely to be endogenous (see Harrison et al., 2014), although it is difficult to find valid exclusion restrictions. The empirical literature suggests several approaches to deal with this such as increased range, clients as source of information, continuous external R&D engagement, R&D intensity, share of market, internal R&D activities, patents or public support for innovation activities (see Crespi et al., 2019; Hall et al., 2008; Harrison et al., 2014; Peters, 2008).

Previous studies: datasets, measurement, coverage and results

Abundant firm-level studies, commonly based on single-country data and often limited to the manufacturing sector point to a positive direct link between product innovations and employment, while the effects of process innovations are more ambiguous (Calvino and Virgillito, 2018; Harrison, et al., 2008, 2014; Van Reenen, 1997; Vivarelli, 2013, 2014 and, 2018). With few exceptions (Barbieri, Piva and Vivarelli 2019; Bogliacino et al., 2012 Lachenmaier and Rottmann, 2011; Van Roy, Vértesy and Vivarelli, 2018, for instance) these studies are based on cross-sectional data on firms and thus cannot control for unobserved firm effects. Also, apart from Harrison, et al. (2008, 2014), Evangelista and Vezzani (2012) as well as Dachs and Peters (2014), large scale cross-country comparisons are scarce. In addition, a considerable number of studies use cross-sectional statistics of the Community Innovation Survey without linking them to any other official firm-level data or over time (Dachs and Peters, 2014; Evangelista and Vezzani, 2012; Harrison et al., 2014).

A selection of studies from 2010 onwards is summarized in Table 2, including information about data sources used, coverage, measurement and results. In general, studies based on linked firm-level data becomes more common over time. An example is the study by Romano (2019), which combines three official Italian micro data sources: the CIS, the business register and the business statistics. Another example is Falk (2015), who uses the Austrian Structural Business Statistics (SBS) linked to the CIS.

Table 2: Selection of recent studies on the link between innovations and employment

		Data source										
	Country	BR	PS/SBS	CIS	Other	Time period	Sector	Level	Measure	Method	Obs.	Result
Barbieri, Piva and Vivarelli (2019)	IT	X	X	X			M	Firm	R&D expenditures, Innovation input expenditures	Static fixed effects models	892	R&D expenditures +, Innovation input expenditures +
Bogliacino, Piva and Vivarelli (2012)	EU countries				Amadeus	1990–2008	M, S	Firm	R&D expenditures	Dynamic panel data models	677	R&D + (higher in high-tech manufacturing)
Dachs and Peters (2014)	16 European countries			X		2002-2004	M, S	Firm	New market product dummy variables, process innovation dummy	OLS	64656	Product innovations + (largest in foreign owned) Process innovations -
Evangelista and Vezzani (2012)	CZ, ES, FR, IT, PT, SI			X		2002-2004	M, S	Firm	Product and process innovation dummies	3SLS	57856	Product innovations +, process innovations +
Falk (2015)	AT		X	X		2004-2008	M, S	Firm	Product and process	OLS quantile	3700	product innovations +, process

									innovation dummy	regressions		innovation 0; higher quantiles
Harrison et al. (2008, 2014)	DE, ES, FR, UK			X		1998-2000	M, S	Firm	Sales growth of new products; process innovation dummy	OLS	19166	Product innovations +, process innovation (+/-)
Herstad and Sandven (2019)	NO			X		2004-2010	M, S	Firm	Product and process innovation dummy	Logistic	4604	Combined product and process innovations +
Lachenmaier and Rottmann (2011)	DE			X	X CIS type	1982-2002	M	Firm	Product and process innovation dummy	Dynamic panel data models	31885	Lagged Product innovations +, lagged process innovation +
Lim and Lee (2019)	KO				X CIS type	199-2009	M	Firm	Sales growth of new products; process innovation dummy	OLS, 2SLS	11000	Product innovation +, process innovation 0
Meriküll (2010)	EE	X		X		1998-2002	M, S	Firm	Product and process innovation dummy	OLS, system GMM	7300	Product innovations +, process innovation +; high-tech : 0
Meschi, Tyamz, Vivarelli (2016)	TY		X			1992-2001	M	Firm	R&D expenditures	Dynamic panel data models	114577	R&D+
Ortiz and Salas Fumás (2019)	ES			X		2003–2014	M, S	Firm	Product and process innovation dummies	Dynamic panel data models	45620	Combined product and process innovations +
Romano (2019)	IT	X	X	X		2010-2015	M	Firm	New market product and process innovation dummy	OLS	3049	Product innovations (+), process innovations +
Van Roy,Vértesy and Vivarelli (2018)	EU-27				ORBIS database with the OECD PATSTAT at	2003-2012	M, S	Firm	Patent applications	Dynamic panel data models	63561	Weighted patents + (only in high tech manufacturing)
Falk and Hagsten (2018)	9 European countries	X	X	X	ICT usage	1992-2010	M, S	Representative firm	Sales of market novelties	System GMM		Market novelties (+)

Notes: BR means business register and PS production survey (SBS). M illustrates manufacturing and S services.

Mitigating data deficits by targeting the representative firm

As highlighted in the previous section, empirical research on employment and innovations encounter several challenges, not only related to the possible channels of impact, but also to comparability, data availability and measurement. Data deficits may stem from several sources. Single datasets such as the Community Innovation Survey are seldom informative enough for impact studies and need to be linked to additional firm-level data, which in turn might originate from sample surveys. Within the European Union, two well-known and well-researched datasets are the CIS and the ICT usage and e-commerce in enterprises (data source h, References). Both these harmonized datasets originate from sample surveys, implying that when merged, the resulting overlap may be much smaller than the original datasets. To reduce the response burden of firms, most EU (or affiliated) countries apply a design with rotating samples. This means that attrition appears over time in addition to issues with cross-sectional overlaps of different datasets. For instance, Szczygielski, Grabowski and Woodward (2017) show that the Polish CIS loses 60 per cent of observations each wave. Stemming from this is a possible bias towards large firms because they are the only ones regularly selected in surveys. Selection bias over time vastly affects the possibility of estimating firm-within effects (Bartelsman, Falk, Hagsten and Polder, 2019; Hagsten, 2016).

Large scale cross-country analyses are commonly not possible to undertake because of legal restrictions relating to disclosure (Bartelsman, et al., 2018). Even with access to firm-level data, there are limitations because of the need for broader information or due to the design of the datasets themselves.

An additional aspect of importance is the data frequency. Business register, production surveys, and the ICT usage in enterprises are all annual surveys, while information on R&D expenditures and innovation activities are often reported on a biennial basis. This may complicate linking of data and create issues with interpretation of variables and results. The CIS, for instance, includes a set of questions where the respondent is expected to give information for three-year periods. At the Eurostat Safe Centre, it is possible to gain access to cross-country CIS data for research purposes, although it is not feasible to use several waves of the survey at a time. This leads to different kinds of assumptions, such as about when in time during the three-year period the new product or market novelties are introduced (Harrison et al., 2008, 2014).

The lack of dynamic and cross-country approaches often has its origin in data deficits. A way to circumvent the impediments of disclosure, sample design et cetera is to use industry or micro-aggregated data (beyond the firm but below industry), where the latter is preferable since it preserves moments collected from firm-level data. These moments represent units of firms such as size-class, innovators, exporters, employees with specific skills et cetera and thus could be considered reflecting the representative rather than the average firm (Bartelsman, et al., 2018). Such data can be retrieved from several (official) sources by use of remote control and a common protocol, which runs on micro-aggregated harmonized and firm-level linked data. The micro-aggregating process may also reduce noise that is often apparent in firm-level data.

Table 3: Descriptive statistics

Year	Employees	Materials, $\overline{\text{m Euro}}$	Pay/ employee, $\overline{\text{m Euro}}$	Sales market novelty, %	Capital stock, $\overline{\text{m Euro}}$	Broadband employee, %	Process innovation, % firms	Organizational change, % firms	Firm groups
				Services					
2002	270516	36570	41	6	21249	53	29	44	31
2004	270472	34301	39	8	19881	60	29	42	38
2006	218913	29614	43	9	19860	62	29	36	52
2008	242390	34282	43	7	23341	65	28	34	56
2010	214368	22609	42	13	23837	64	24	32	43
				Manufacturing					
2002	71713	12648	41	5	6224	26	37	42	78
2004	75542	12495	37	7	5637	32	35	40	94
2006	63436	11068	40	8	5778	37	36	36	126
2008	65224	12222	40	7	6623	41	34	33	126
2010	45782	8398	42	8	7034	46	30	33	96

Notes: $\overline{\text{m Euro}}$ means million Euro in constant prices.
Source: Micro Moments Database.

The share of market novelties ranges from six to 13 per cent in service firms, and from five to eight per cent in manufacturing firms (Table 3) On average, process innovations are more common in manufacturing, while organizational changes are equally common independent of industry. Broadband connectivity among the employees is far more used in service firms.

Labor demand model for the representative firm

By use of micro-aggregated harmonized multi-linked firm-level data, available in for instance the Micro Moments Database (Bartelsman, Hagsten and Polder, 2018; (data source i, References), the relationship between technological innovations and labor demand can be studied. The linking of different sources allows a broader set of variables than in the mainstream literature, the aggregation deals with both issues of disclosure and rotating datasets while the slight drawback is the move from the average firm to the representative. An investigation of the relationship between new market product (market novelty) sales and labor demand (employment) in nine European countries will be used as an example (Falk and Hagsten, 2018), completed with new alternative estimations.

The rich dataset at hand allows the labor demand equation to be derived from the non-homothetic CES cost function (Borjas and Van Ours, 2010; Hamermesh, 1993; Van Reenen, 1997). In this study, output is distinguished between turnover of market novelties and turnover of existing products. The two variable inputs are labor and total materials, including energy. With subscripts *i* for industry and *t* for time suppressed, the cost function is specified as follows (see Chambers, 1988; Falk and Hagsten, 2018):

$$C(W, P_M, Y_1, Y_2) = \left(A_1 W^{\rho} Y_1^{\alpha_1} Y_2^{\beta_1} + A_2 P_M{}^{\rho} Y_1^{\alpha_2} Y_2^{\beta_2}\right)^{\frac{1}{\rho}} \tag{1}$$

Where W is the average cost per employee, P_M reflects the price index of materials, Y_1

stands for turnover of new market products and Y_2 is the turnover of existing products. The technology level is illustrated by *A*, the substitution parameter is denoted by ρ and σ is the elasticity of substitution between the two types of inputs $\sigma = (1-\rho)$. Absolute values of σ close to zero indicate limited substitution while values approaching infinity imply a high degree of substitutability. Since the production technology is non-homothetic, total costs are a function of output. The factor demand equations for labor L^* and material inputs in constant prices M^* can be obtained by applying Shephard's lemma:

$$
\begin{aligned}
L^* &= \frac{\partial C}{\partial W} = \frac{1}{\rho}\left(A_1 W^{\rho} Y_1^{\alpha_1} Y_2^{\beta_1} + A_2 P_M{}^{\rho} Y_1^{\alpha_2} Y_2^{\beta_2}\right)^{\frac{1}{\rho}-1} \rho A_1 W^{\rho-1} Y_1^{\alpha_1} Y_2^{\beta_1} \\
&= C^{1-\rho} A_1 W^{\rho-1} Y_1^{\alpha_1} Y_2^{\beta_1}
\end{aligned}
\tag{2}
$$

and

$$
\begin{aligned}
M^* &= \frac{\partial C}{\partial P_M} = \frac{1}{\rho}\left(A_1 W^{\rho} Y_1^{\alpha_1} Y_2^{\beta_1} + A_2 P_M{}^{\rho} Y_1^{\alpha_2} Y_2^{\beta_2}\right)^{\frac{1}{\rho}-1} \rho A_2 P_M{}^{\rho-1} Y_1^{\alpha_2} Y_2^{\beta_2} \\
&= C^{1-\rho} A_2 M_2^{\rho-1} Y_1^{\alpha_2} Y_2^{\beta_2}
\end{aligned}
\tag{3}
$$

The relative labor demand function is then achieved by dividing the labor equation by the material inputs equation and taking the natural logs on both sides. Substituting $(\rho - 1)$ by $-\sigma$, adding an error term ε and assuming that relative employment increases proportionally with relative output leads to the following regression equation:

$$
\ln\frac{L_{it}}{M_{it}} = \ln\frac{A_1}{A_2} - \sigma \ln\left(\frac{W_{it}}{P_{M,it}}\right) + \eta \ln\left(\frac{Y_{1,it}}{Y_{2,it}}\right) + \varepsilon_{it} \, , \tag{4}
$$

where *i* denotes sector and *t* time equals to 2002, 2004, 2006, 2008 and 2010. This specification can be augmented by a set of innovation indicators reflecting new processes, products or organizations (Antonucci and Pianta, 2002; Biagi and Falk, 2017; Mastrostefani and Pianta, 2009), measures of investment in tangible assets like R&D

expenditures (Bogliacino et al., 2012) or the intensity with which the employees use ICT innovations (Falk and Hagsten, 2018). Given that the micro-aggregated firm-level multi-linked dataset takes the form of a panel over time, either static or dynamic panel data models can be estimated.

By use of a system GMM estimator, Falk and Hagsten (2018) demonstrate that turnover of market novelties (relative to existing ones) has a significant impact on relative employment for the period 2002-2010 in manufacturing firms, although there is no equivalent effect for service firms. Instead there is a strong link between employment and technology use (broadband connectivity in these firms). Fixed effects estimations based on the same dataset, with an identical specification reveal similar results (Table 4).

Table 4: Fixed effects estimates of the impact of market novelties on relative labor demand

			Manufacturing			
	Coeff.		t-stat	Coeff.		t-stat
ln relative wage (t)	-0.64	***	-10.35	-0.63	***	-10.30
ln ratio of turnover new market products (t)	0.03	***	2.69			
Ratio of turnover new market products (t)				0.34	**	2.52
ln capital stock (t)	0.03		1.44	0.02		1.22
Broadband internet connected employees (t)	-0.04		-0.39	-0.02		-0.26
Process innovations, % (t)	0.00		-0.03	0.01		0.12
Organizational changes, % (t)	0.15		1.28	0.14		1.22
Constant	-2.90	***	-8.09	-2.96	***	-8.06
Year dummy variables	Yes			Yes		
R^2 within	0.60			0.60		
Number of observations	520			520		
Number of groups (countries)	126 (8)			126 (8)		
			Services			
	Coeff.		t-stat	Coeff.		t-stat
ln relative wage (t)	-1.17	***	-5.45	-1.18	***	-5.72
ln ratio of turnover new market products (t)	0.00		0.03			
Ratio of turnover new market products (t)				-0.05		-0.43
ln capital stock (t)	-0.23	***	-8.30	-0.23	***	-8.46
Broadband internet connected employees (t)	0.60	***	3.32	0.53	***	3.10
Process innovations, % (t)	0.50		1.46	0.20		0.70
Organizational changes, % (t)	-0.35		-1.01	-0.26		-0.87
Constant	3.03	***	3.06	3.21	***	3.43
Year dummy variables	yes			yes		
R^2 within	0.43			0.43		
Number of observations	220			228		
Number of groups (countries)	58 (8)			58 (8)		

Notes: The dependent variable is the logarithm of the ratio of employment to material inputs in constant prices. Asterisk ***, ** and * denote significance at the 1, 5 and 10 per cent level.
Source: Micro Moments Database and own calculations.

An increase in the ratio of turnover of market novelties to existing ones by one percentage point is associated with a rise in relative labor demand by 0.33 per cent. Variables reflecting process innovations, organizational change and capital stock are not significantly related to relative labor demand. Just like the GMM estimation, the broadband employee variable is significantly linked to labor demand for the representative service firm. The magnitude is similar to that of the GMM estimation: a one percentage point increase in the proportion of employees with broadband internet access coincides with a 0.5 per cent surge in relative labor demand. Similar magnitudes are not, however, the case with the impact of the innovation variables, where the fixed effects regression renders somewhat smaller estimates, but still with the same pattern. The results support the general picture in literature that product innovations potentially raise employment. However, this specific approach also has the advantage of including a wide range of firm characteristics such as size, international experience and intensity of ICT usage. Falk and Hagsten (2018) demonstrate that market novelties only relate to employment in small firms (10-49 employees), while the employee use of a technological innovation, broadband connectivity in this case, is solely relevant in medium-sized and large firms (+50 employees).

Summary

In this chapter, common methods and datasets for analyses of the link between labor demand and technological innovations are discussed. Firm-level linked datasets are generally more beneficial for the analysis, but may suffer from small overlaps or attrition over time, if they are at all disclosed. Comparability across countries is often complicated since there are no official sources where cross-country data is stacked in one single set. To overcome several of these issues, an approach is suggested where the analysis focuses on the representative firm instead of the average. Data on this firm can be retrieved by use of a common protocol that links and micro-aggregates harmonized official multi-linked firm-level data. Estimation results from this approach for nine European countries and the period 2002-2010 reveal that the turnover of new market products has a significant positive impact on relative employment in the representative manufacturing firm, although there is no similar relationship with the representative service firm. Instead the intensity with which ICT is used (broadband internet connected employees) is significant and positive in this firm. The results follow the trend in the firm-level literature, confirming that analyses of the representative firm are applicable. They also allow a broader range of variables and comparability across countries.

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