Technology shocks and sectoral labour market dynamics

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Abstract

The past few decades have witnessed a rapid employment growth in sectors characterised by an increased use of productivity-enhancing technologies, together with a slowdown in more traditional sectors. Using data on twelve US industries, over the 1992-2013 period, we estimate a multi-sector model of gross job flows and investigate to what extent *neutral* and *investment-specific* technology shocks affect sectoral labour market dynamics. We propose a new identification strategy for these two technology shocks based on statistical evidence combined with an original empirical specification. The results indicate that positive investment-specific technology shocks have favourable employment consequences, increasing job creation and decreasing job destruction in most sectors. However, in response to neutral technology shocks we do not find clear-cut evidence of overall employment reallocation, which would have supported the creative-destruction dynamics hypothesis. Despite revealing a high degree of heterogeneity, at the aggregate level our findings are consistent with the wealth of existing empirical literature.

JEL: E24, J60, O33.

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1. Introduction

Market economies are constantly affected by structural and cyclical changes, during which substantial adjustments in terms of flows in and out of employment occur. In the past few decades, sectors characterised by an increased use of productivity-enhancing technologies have mostly grown, while others have shrunk. These long-run shifts have been regarded as being to a large extent the consequence of structural forces, and one of the most important drivers is technological progress, on which we focus in this paper. While there are numerous mechanisms that allow technology to affect labour market outcomes, this paper is concerned with two of the most important ones: *investment-neutral* and *investment-specific* technology shocks. An easy and intuitive description is provided in Tassey (1999), according to whom new technologies could spill over in the form of increased *general knowledge* thus fostering more efficient production methods and practices (i.e. *knowledge spillovers*), or in the form of *lower prices* for final and intermediate goods, particularly capital goods (i.e. *price spillovers*).

Several studies try to characterize labour market dynamics with respect to variations in the rate of technological change. Most of them use versions of the classical growth model with vintage capital, as in Solow (1960) and Fisher (2006), where technological progress can be either (i) *disembodied* in the form of better management practices and production methods, i.e. investment-neutral, or (ii) *embodied* in new capital goods and equipment, i.e. investment-specific. This approach coupled with a search and matching framework in the spirit of Diamond (1981) and Mortensen and Pissarides (1994), can offer important insights into labour market responses to technological advances. Recent contributions to this literature are Michelacci and Lopez-Salido (2007); Canova et al. (2010, 2013); Postel-Vinay (2002). A richer model specification can be found in Hornstein Krusell and Violante (2005; 2007), although the authors focus more on wage inequalities and job-match heterogeneity. The general equilibrium models proposed in Justiniano et al. (2010, 2011) and Kaihatsu and Kurozumi (2014) include a more detailed structure of the banking sector, so as to take into account the importance of financial shocks in addition to investment-specific shocks.

In all these papers, technological progress adversely affects worker flows into and out of employment. If firms can update their technology fast and/or costless, then obsolescence would be delayed, but if updating is costly and technological choices are irreversible, then the outcome would bear more with the creative-destruction (Schumpeterian) dynamics. How costly is the process of updating obsolete capital then becomes crucial for the short- and the long-run movements in employment. On the one hand, if old jobs cannot easily upgrade, they become technologically obsolete and firms find it more profitable to destroy them and create new ones, which incorporate the newest technology by default. In this scenario, however, the presence of labour market frictions impedes faster reallocation and it might cause unemployment to increase over the short-term. On the other hand, when updating is cheaper, capital investment will follow together with higher job creation and lower destruction, spurring an expansionary phase with increased employment, investment and output.

This literature is mainly concerned with explaining fluctuations in aggregate variables and abstract from changes occurring at more disaggregated level. Since employment in the manufacturing sector of developed economies has been growing more slowly or even decreasing compared to employment in the service sectors, it would be interesting to search for a more detailed explanation. This is the focus of the present paper: to explore the responses of sector-specific job flows to different technology shocks and see how this relates to aggregate dynamics. In particular, we are interested in investigating to what extent neutral and investment-specific technology shocks affect both sectoral and aggregate job flows, and in particular employment. Our paper aims thus at offering a much-needed disaggregated picture of the US employment.

We estimate a multi-sector model of the US labour market using the global VAR (henceforth GVAR) model developed by Pesaran et al. (2004) and Dees et al. (2007). This approach allows us to propose a new identification strategy for the two aforementioned technology shocks, based on some quite intuitive and simple statistical evidence. In particular, we formulate assumptions with respect to the *origin* of each technology shock and attribute it to a particular economic sector.

Firstly, the neutral technology shock (which is akin to an overall TFP shock) originates in what we identify as the R&D sector - the main provider of research output that pushes the technological frontier further. Under the assumption of costly technological updating, neutral technologies allow better production and management methods, better supervision and organization of the activities, thus raising productivity over the long-term. To identify the R&D sector, we draw on statistical evidence that shows a high concentration of research intensity together with a very dynamic high-skilled employment in economic sectors such as *information* and *professional, scientific and technical services*.[1] While Canova et al. (2010, 2013), Michelacci and Lopez-Salido (2007) and Fisher (2006) use long-run restrictions on the variance decomposition of productivity in a VAR-type model, our neutral technology shock

[1] *Professional, scientific and technical services* and *Professionals* might be used interchangeable in the text; both refer to North American Industry Classification System (NAICS) code 54.

is derived directly from a theoretically-based *knowledge production function* specified as in Ha and Howitt (2007), Abdih and Joutz, (2006), Madsen (2008), Ang and Madsen (2011) and Venturini (2012). We employ patent data as a proxy for innovation output, and relative employment in the R&D sector as a proxy for innovation input.

Secondly, the investment-specific technology shock (which is akin to a relative TFP shock in a two sector economy, see Hornstein et al., 2005) is assumed to originate in the intermediate sector, which we identify as the manufacturing sector. This modelling assumption is supported by the fact that manufacturing produces most of the new capital goods, such as equipment, instruments, and machines, which can immediately embody the newest available technology. Through continuous investment, this new capital will eventually replace the old vintages and technology will spread out, facilitating the production of various other consumption goods (including services) in more efficient ways.

Labour markets in our model are characterized by search and matching frictions both within and across economic sectors. Firms that belong to a given sector, over the short-run post vacancies and hire workers by tapping into the pool of the unemployed individuals with sector-specific skills. Workers reallocation across sectors is allowed in the medium- and long-run. These mechanisms can be easily reflected in our empirically GVAR specification of a model that relies on a few sector-specific endogenous variables, namely employment and job flows.

Our findings indicate that neutral technology shocks have negative overall effects on employment, while investment-specific technology shocks are generally expansionary. In line with our expectations, job creation and destruction respond differently to shocks: flows out of employment are slightly more sensitive to technology shocks (especially investment-specific) than flows into employment. While we do not find clear-cut evidence of employment reallocation in response to neutral shocks, results indicate that investment-specific technology shock do increases job creation and decreases job destruction in most sectors.

This paper is organized as follows. Section 2 show the data used in this paper. Section 3 describes the model specification and the empirical approach. Section 4 presents and discusses the results. Concluding remarks are given in section 5.

2. The data

We use a sample of US quarterly data from 1992 Q3 to 2013 Q4 on sector-specific employment and job flows. One limitation comes from the fact that gross job flows at sectoral level are available only since 1992:Q3.[2] Our dataset spans across 13 economic sectors identified at two-digit level in the NAICS system, thus including all existing sectors, except agriculture and public administration. However, we combine *information* (NAICS 51) and *professional, scientific and technical services* (NAICS 54) into a single economic sector, which we label as the *R&D* sector; this leaves us with a total of 12 distinct economic sectors. Our choice is supported by statistical evidence that shows a higher concentration of technology advances, R&D intensity and more dynamic pattern of employment both in the *information* and *professional, scientific and technical services* (see Appendix A).

We follow the previous literature to identify the investment-specific technology shock as an unexpected change in the price of investment goods (capital and new equipment) relative to consumption goods. The relative price index is constructed as a ratio between the deflator for non-residential investment in equipment and the overall GDP deflator.[3] As a robustness check, we also consider the more general deflator of non-residential investment (which includes structures and intellectual property products, in addition to equipment). In our setting, manufacturing is the intermediate sector that produces and sells to all other sectors new capital goods with the newest technology already incorporated. An investment-specific technological advance is defined as a decrease in the price of capital goods relative to consumption goods, so that all the other producers (both goods and service-providers) will be able to increase their investment buying cheaper but technologically updated capital vintages.

The neutral technology shock is expressed in terms of unexpected change in the number of patent applications by US residents. The Schumpeterian perspective on the endogenous growth theory has gained a lot of empirical support recently both for the US and for other developed and developing countries. Ha and Howitt (2007), Abdih and Joutz (2006), Madsen (2008), Ang and Madsen (2011) and many others have provided empirical support using time-series methods (e.g. cointegration) and historically long patent data as a proxy for innovation output. We adopt a similar approach here based on an empirical approximation of a *knowledge production function*. Accordingly, we model the flow of patents (or ideas) and the stock of patents (or existing knowledge) simultaneously, along with some measure of

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[2] Data available from U.S. Bureau of Labor Statistics, Business Employment Dynamics at http://www.bls.gov/bdm/.

[3] Our relative price index is slightly different than the quality-adjusted price index for new equipment used by Cummins and Violante (2002), Michelacci and Lopez-Salido (2007), Canova et al (2010, 2013). We have preferred an indicator with a broader coverage to include most of the goods produced by the manufacturing sector. In this respect our indicator is more similar to the one used by Justiniano et al (2011) and Kaihatsu and Kurozumi (2014). It also allows us to have a more general perspective over the transmission mechanisms at work in a multi-sector setting.

research input (in our case the R&D sector employment as a proxy for the number of scientists and researchers) and product proliferation (in our case total employment outside the R&D sector). Annual patent data come from the US Patent and Trademarks Office (PTO) and are available from as early as 1800s, while quarterly data are taken from the World Intellectual Property Organization (WIPO) and begin with 1990:Q1.

To measure the flow of US patent applications, we draw directly on WIPO data and use the US patent applications filled under the Patent Cooperation Treaty (PCT) that allows an application to be simultaneously recognized in 148 countries across the globe. This way of measuring disembodied technological progress is consistent with the discussion in Hornstein and Krussell (1996) and Cummins and Violante (2002). However, to construct a quarterly time-series for the stock of patents, we had to rely on historical data and combine information from both datasets using the perpetual inventory method. To obtain an initial value for knowledge at the end of 1992 (approximately the start date in our sample), we use the time-series available for annual patent applications from US PTO, assume that the stock of knowledge was zero in 1850 and cumulate the flow of patent applications (both US and foreign) using a rate of 15% annual depreciation until 1992.[4] We obtain a ratio of patent applications to knowledge (i.e. flow to stock ratio) in 1992 of approximately one fifth, which we use as an input to derive the value of *unobserved stock of patents* consistent with observed WIPO quarterly data. We apply the same perpetual inventory method and annual depreciation rate (but quarterly compounded this time) to cumulate quarterly PCT patents from top 10 innovation-leading countries (as classified by WIPO), i.e.: Switzerland, China, Germany, France, United Kingdom, Japan, Republic of Korea, Netherlands, Sweden, and the US.

3. The econometric model

This section describes the econometric model and the empirical approach used to identify the neutral and the investment-specific technology shocks. The global VAR modelling framework allows us to rely on a multi-sector model specification that can better reflect the transmission of technological advances on labour market dynamics and their inter-sector spillovers. We estimate the model, check its properties and evaluate its dynamics by studying the generalized impulse response functions (GIRFs) to both technology shocks. We rely on generalized variance decompositions (GFEVDs) to gain insights into the sensitivity of employment and job flows to various shocks.

[4] We take the annual depreciation rate at 15% similar to Abdih and Joutz (2006); as a robustness check, lower depreciation rates (10%) have provided qualitatively similar results.

Job creation and destruction flows (both measured as headcounts) are expressed as positive and negative employment changes over a quarter, computed at the establishment/firm level. We specify the basic model in logs of employment (E) and job creation (C) or, alternatively, employment (E) and job destruction (D). Up to an inconsequential approximation we can write the same linear relation in logs: $\Delta E = C - D$. With the change in employment following a stationary process, gross creation and destruction flows will follow a long-run cointegrating relation (see Caballero and Hammour, 2005). To exploit this low-frequency restriction, we estimate a sector-specific bi-VAR model specification using only E and C as endogenous variables, thus allowing for a potential cointegrating vector between these endogenous variables.[5] In contrast to Canova et al. (2009, 2013), we are able to work with (all) our variables in levels, without first-differentiating them. Canova et al. (2009, 2013) document an important stochastic component in their variables, but prefer to work with data in first-difference and provide evidence for a lack of empirical consequences on the results deriving from this transformation. In our case, since preliminary unit root tests (Augmented Dickey-Fuller, ADF, and Weighted-Symmetric Dickey Fuller, WSDF) suggest that the presence of a unit root cannot be rejected for both E and C in a majority of sectors, we decide to specify the model in error-correction terms.

The 12 sector-specific VAR models are aggregated in order to gain insights into relevant sectoral spillover effects. Following the methodology proposed by Pesaran et al (2004) and Dees et al (2007), we can control for common unobserved factors by including the sector-specific external counterparts (the * starred terms) of the endogenous variables, practically transforming the VAR-type model into a VARX-type. Note that for each sector, we include only the starred employment level (E*) computed as a weighted average of employment levels in the other sectors, where E* might stand as a proxy for the pool of unemployed individuals with no sector-specific skills.

Besides the labour market specific variables E, C and E*, the model specification includes the following weakly exogenous variables, which are necessary to identify the two technology shocks: US patents applications (denoted by A), world knowledge stock (denoted by K), the relative price index (denoted by Q) and the real non-residential investment as a share of GDP (denoted by G). In the GVAR terminology, these variables are labelled as *global* variables and enter as endogenous only in the R&D and manufacturing, while

[5] In the alternative specification we replace creation, C, with destruction, D, as a second endogenous variable. However, to keep the discussion straightforward, the model specification discussed here refers to the baseline with C and E as endogenous.

exogenous in all other sectors and in any estimated long-run cointegrating vector. Accordingly, except manufacturing and R&D sectors, the general VAR(X) model specification for any given economic sector can be written as following:

$$(1)\qquad \begin{pmatrix} \Delta E_t \\ \Delta C_t \end{pmatrix}^s = \alpha\beta \begin{pmatrix} E_{t-1} \\ C_{t-1} \\ {E^*}_{t-1} \\ A_{t-1} \\ K_{t-1} \\ Q_{t-1} \\ G_{t-1} \end{pmatrix}^s + \sum_i \gamma(i) * \begin{pmatrix} \Delta E_{t-i} \\ \Delta C_{t-i} \end{pmatrix}^s + \sum_k \theta(k) * \begin{pmatrix} \Delta {E^*}_{t-k} \\ \Delta A_{t-k} \\ \Delta K_{t-k} \\ \Delta Q_{t-k} \\ \Delta G_{t-k} \end{pmatrix}^s + {\epsilon^s}_t$$

where the sector is indexed by the superscript *s*, lag lengths are denoted by *i* and *k*, while the Greek letters denote the parameters to be estimated. In this respect, our list of variables is mostly similar to Canova et al. (2009), except for the lack of productivity (a proxy for TFP), which we have replaced by patents.

For model specification (1), we expect at most one cointegrating vector for each sector level, corresponding to the long term relation between job creation, C, and destruction, D, as in Caballero and Hammour, (2005). As mentioned before, all sectors producing final goods and services share the specification above, except for the manufacturing (intermediate) sector and the R&D sector (information together with professionals and business services). Below, we explain the main differences in specification that arise between sectors, essentially due to our comprehensive multi-sector approach.

The R&D sector includes both, the flow and the stock of patent applications (A and K respectively) as endogenous. The specification of the R&D sector-specific VAR model becomes:

$$(2)\qquad \begin{pmatrix} \Delta E_t \\ \Delta C_t \\ \Delta A_t \\ \Delta K_t \end{pmatrix}^{rd} = \alpha\beta \begin{pmatrix} E_{t-1} \\ C_{t-1} \\ {E^*}_{t-1} \\ A_{t-1} \\ K_{t-1} \end{pmatrix}^{rd} + \sum_i \gamma(i) * \begin{pmatrix} \Delta E_{t-i} \\ \Delta C_{t-i} \\ \Delta A_{t-i} \\ \Delta K_{t-i} \end{pmatrix}^{rd} + \sum_k \theta(k) * \begin{pmatrix} \Delta {E^*}_{t-k} \\ \Delta Q_{t-k} \\ \Delta G_{t-k} \end{pmatrix}^{rd} + {\epsilon^{rd}}_t$$

According to the insights provided by Ha and Howitt (2007), Abdih and Jourtz (2006), Madsen (2008) and Ang and Madsen (2011), there is a second cointegrating relation[6] expected to hold in the R&D sector. This cointegrating relation corresponds to the knowledge

[6] A stylised knowledge production function takes the following form: $\frac{A}{K} = \lambda \left(\frac{E}{E^*}\right)^{\sigma} K^{\phi-1}$ where we have used the current notations of the variables in order to ease the understanding; the Greek letters are model coefficients, E is a proxy for innovation input and E* is a proxy for product proliferation.

production function, where the *research intensity* in our case would be measured in terms of R&D employment relative to *starred* employment, E*. Therefore, the second long-run cointegrating vector would be associated with a knowledge production function in the R&D sector and should include A, K, E and E*.

Relative prices, Q, and the real investment share are endogenous only in the manufacturing sector specification, but weakly exogenous for all the other sectors. This happens because the intermediate sector provides the basic intermediate (capital) goods latter used in the production of all the final goods and services. In case of an investment-specific technology shock, we expect the relative price of new capital and equipment to go down, when expressed in terms of final consumption goods prices (i.e. decrease in Q would mean cheaper capital goods). The specification of the manufacturing sector is given by:

$$(3) \qquad \begin{pmatrix} \Delta E_t \\ \Delta C_t \\ \Delta Q_t \\ \Delta G_t \end{pmatrix}^{man} = \alpha\beta \begin{pmatrix} E_{t-1} \\ C_{t-1} \\ E^{*}_{t-1} \\ A_{t-1} \\ K_{t-1} \\ Q_{t-1} \\ G_{t-1} \end{pmatrix}^{man} + \sum_i \gamma(i)^* \begin{pmatrix} \Delta E_{t-i} \\ \Delta C_{t-i} \\ \Delta Q_{t-i} \\ \Delta G_{t-i} \end{pmatrix}^{man} + \sum_k \theta(k)^* \begin{pmatrix} \Delta E^{*}_{t-k} \\ \Delta A_{t-k} \\ \Delta K_{t-k} \end{pmatrix}^{man} + \epsilon^{man}{}_t$$

A second cointegrating vector involving Q and G could be expected to hold in the manufacturing sector, associated with a demand function for capital goods relative to consumption goods (as an inverse of the relative price index). This is indeed what we find to be the case in all of the model specifications we employ.

Models (1)-(3) can be stacked together and estimated efficiently in a GVAR framework as in Pesaran et al. (2004) and Dees et al. (2007). To combine the sector-specific estimated VARs, we use fixed weights derived from the US input-output matrix corresponding to year 2002, available from the US Bureau of Economic Analysis (BEA).

4. Empirical results

As already discussed in section 3, unit root tests confirm that, for the large majority of NAICS sectors, the logs of employment, creation and destruction time series are integrated of order one, i.e. they have a unit root. We select the lag length (allowing for a maximum of 4) for each sector-specific model in order to avoid residual serial correlation based on standard F-tests. Next, we test for cointegration and find at most one relation for most sectors (as expected, and in line with findings from Caballero and Hammour, 2005). There are two exceptions however, the R&D and the Manufacturing sectors, where our expectations of finding more than one cointegrating vectors are confirmed (see discussion in the previous section).[7] The final model is estimated in error-correction form, which properly preserves the unit roots of the original model. We do not impose over-identifying restrictions on the cointegrating vectors in the case of R&D and Manufacturing sectors for as long as the model dynamics remains stable. We rigorously check the number of eigenvalues with modulus equal to one, the persistence profiles to system-wide shocks, and the number of estimated cointegrating vectors.

Our main empirical results build on generalized impulse response functions (GIRFs) to shocks in patents (A) and relative prices (Q), our proxies for neutral and investment-specific technology shocks, respectively. Figure 1 presents generalised impulse-response functions for the overall economy (i.e. aggregation of the 12 economic sectors). Panel A presents results from the baseline specification, where employment and job creation are the endogenous variables, while Panel B shows result from the alternative model specification, where creation is replaced with destruction. Since destruction flows do not directly enter the baseline model specification, they have been reconstructed for illustration purposes using steady-state values and the relation between C, D and changes in E. Likewise, in the alternative specification where destruction flows are endogenous, creation flows have been reconstructed in a similar fashion.

Our findings are broadly consistent with the wealth of existing empirical evidence (Michelacci and Lopez-Salido 2007; Canova et al. 2010, 2013). In aggregate terms, in response to neutral technology shock job destruction increases while creation rate decreases allowing employment to fall over the short-run, but then return close to equilibrium over the long-run. In response to an investment-specific shock instead, destruction substantially decreases while job creation increases allowing employment to gradually rise over time. Investment share also increases facilitating technology diffusion as expected.

Sector-specific GIRFs in response to a neutral technology shock are reported in Figure 2. To generate confidence bands, we use 5000 bootstraps of the estimated GVAR model and use the 90% as a threshold for our discussion. It is worth noting however, that GIRFs with wide confidence bands are a well-known outcome in many estimated GVAR models (see Pesaran and Smith, 2006), with some authors proposing using as low as 50% confidence bands to interpret results (Chudik and Fratzscher, 2012). In this context, we see our empirical findings

[7] Results are not reported, but available upon request.

below as lying on the conservative side, thus strengthening the argument that identifying shocks by origin can be a successful empirical strategy.

As it is clear from Figure 2, while employment decreases over the short-run in most of the sectors, statistically significant declines are found in transportation but marginally significant in construction, manufacturing and even the R&D sector. Interestingly, the only sector that actually registers an increase in employment is the education and health sector, although this is not statistically significant. However, we do not find clear evidence of reallocation, defined as simultaneous positive creation and destruction, except for very few sectors such as mining, utilities and leisure. Short-lived but statistically significant negative responses from creation are found in the majority of sectors.[8]

The sector specific GIRFs to an investment-specific technology shock are reported in Figure 3. In response to a shift in the relative price of capital goods to consumption goods, employment responds positively and this result is statistically significant up to 10 quarters ahead in the majority of the sectors. In particular employment in the financial sector seems to permanently move to a higher path. Job creation significantly raises for up to 8 quarters ahead in most of the sectors, while destruction shows statistically significant declines for 4 to 6 quarters ahead in 8 out of 12 sectors.

Other interesting results can be illustrated with variance decomposition methods. We follow Pesaran et al (2004) and Dees et al (2007) who recommend the use of generalized forecast error variance decomposition (GFEVD) in a GVAR setting. Results for this exercise with respect to employment, creation and destruction flows are reported in Figure 4. For each sector, all three labour market variables appear more sensitive over the long-run to influences arising from outside their sector; while, over the short-run sector-specific dynamics and persistence dominate their variance decomposition. Real investment and relative prices have a higher contribution to the variance decomposition of E, C and D over the medium-to-long-term, more so in the case of C and D. Destruction seems to be slightly more sensitive than creation to relative prices and real investment shocks. Even after 20 quarters, some sectors such as construction, utilities and education and health seem to be less sensitive than others to outside influences arising from variations in employment elsewhere.

To reassure the validity of results a number of robustness checks have been carried out. In particular, we have:

[8] Comparatively, short-lived and positive statistically significant destruction is found only in the transportation sector in the alternative specification.

- used a 10% depreciation rate to accumulate patents and re-construct a different stock measure (as a proxy for knowledge);
- excluded non-US patents and re-constructed a different patent stock measure (knowledge) for US only (as if US knowledge would build solely on domestic knowledge with no foreign influences), in contrast to using data from the top 10 leading-innovation countries.
- used the broadest measure of non-residential investment (which also includes structures and intellectual products along with equipment) to derive a relative price index (based on the relative deflators of investment and GDP) as a proxy for the cost of the new capital goods produced by the manufacturing sector.

In all these cases, the results were qualitatively similar.

5. Conclusions

The last few decades have witnessed important structural changes, during which substantial employment adjustments in terms of workers flows in and out of employment have occurred. Sectors characterised by an increased use of productivity-enhancing technologies have grown, while others have shrunk. Overall, technological progress has had significant consequences across all industries and activities. Using data on twelve US economic sectors, we estimate a multi-sector model of gross job flows and investigate to what extent neutral and investment-specific technology shocks affect sectoral labour market dynamics.

This paper makes at least two main contributions. Firstly, we confirm that neutral and investment-specific technology shocks have very different employment consequences on US aggregate labour market dynamics over the 1992-2013 period. Moreover, we illustrate the large existing heterogeneity of sectoral job flows adjustments in response to technology shocks. While we do not find clear-cut evidence of employment reallocation in the aftermath of neutral shocks - to support the creative-destruction dynamics hypothesis -, our empirical results do indicate that investment-specific technology shocks increase job creation and decrease job destruction in most sectors, in line with the existing empirical literature.

Secondly, we propose a novel identification strategy for technology shocks by placing the origin of each shock in a very specific industrial sector, which we select based on available statistical evidence. These two specific sectors are then modelled in greater details to allow identification. This strategy could expand the list of traditional identification approaches implemented in the existing *global VAR* empirical literature (e.g. based on sign or long-run restrictions). Moreover, this approach could be straightforwardly extended to the analysis of other relevant shocks, e.g. the ones pertaining to financial and/or energy sectors.

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Appendix A

Table A.1. R&D employment, by industry (data for U.S. selected industries)

	NAICS code	Total R&D employees (thousands)	R&D employees (% in total)	Patent applications (counts)	R&D performed and paid for by the company / net sales (R&D intensity, %)
All industries	21-22, 31-33, 42-81	1471	7.6	135 958	3.3
Manufacturing	31-33	865	8.7	82 878	3.8
Mining	21	11	3.9	2 872	0.5*
Utilities	22	2	0.4	128	0.1*
Wholesale trade	42	16	5.0	6 958	0.9*
Information	51	232	12.3	16 615	4.4
Finance and insurance	52	26	1.8	1 126	0.4
Professional, scientific and technical services	54	270	13.7	12 062	10.0

Source: National Science Foundation, National Center for Science and Engineering Statistics and U.S. Census Bureau, Business R&D and Innovation Survey, 2011 (Table 31, 32 and 38 available at http://www.nsf.gov/statistics/2015/nsf15307/pdf/nsf15307.pdf). Data on R&D intensity (last column) are from Business R&D and Innovation Survey, 2012

* Business R&D and Innovation Survey, 2011 data.

Table A.2. Total U.S. employment dynamics, by industry.

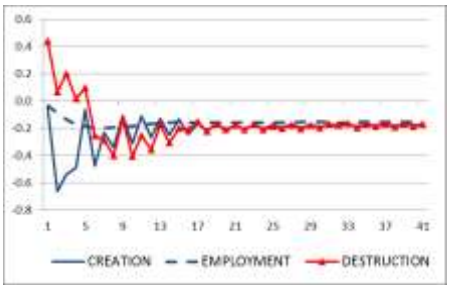
	% change in employment (headcounts)			Average job creation (%)		
	1992:Q3-2013:Q4	**1992:Q3-2000:Q4**	**2001:Q1-2013:Q4**	**1992:Q3-2013:Q4**	**1992:Q3-2000:Q4**	**2001:Q1-2013:Q4**
Natural resource & mining	29.6	-11.2	45.4	17.5	19.8	16.0
Construction	28.4	48.7	-14.1	12.6	14.5	11.4
Manufacturing	-28.3	2.5	-29.3	4.2	4.9	3.7
Wholesale trade	13.6	15.9	-1.0	5.9	6.9	5.3
Retail trade	18.7	19.7	-0.9	7.1	8.1	6.4
Transportation & warehousing	30.9	28.5	2.1	6.2	7.1	5.6
Utilities	-23.8	-17.1	-8.0	2.6	2.7	2.5
Information	1.8	39.9	-27.7	5.7	7.0	4.9
Financial activities	20.4	19.2	0.4	5.8	6.6	5.3
Professional, scientific and technical services	70.9	53.0	12.0	8.7	9.9	7.9
Education and health services	77.0	28.4	36.4	5.0	5.5	4.6
Leisure & hospitality	52.3	26.1	20.2	9.7	10.8	9.0

Source: U.S. Bureau of Labor Statistics.
Note: We split the whole 1992-2013 sample in two sub-samples in order to account for the 2000/2001 dot.com bubble burst that had major consequences on the Information sector activity in terms of employment, number of firms, etc.

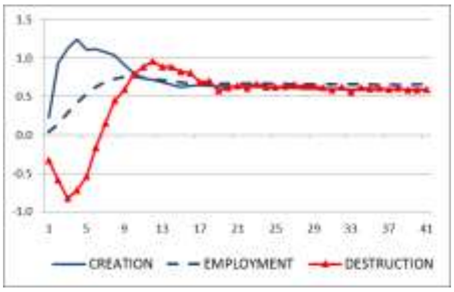
Figure 1. Generalized impulse response functions

Panel A. Baseline specification with employment and creation as endogenous

Neutral technology shock

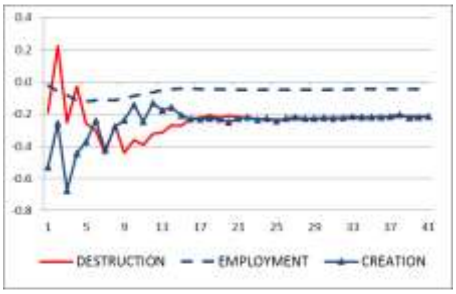


Investment-specific technology shock

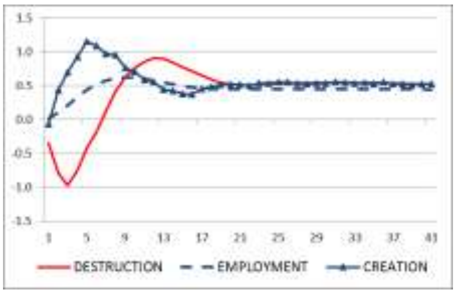


Panel B. Alternative specification with employment and destruction as endogenous

Neutral technology shock



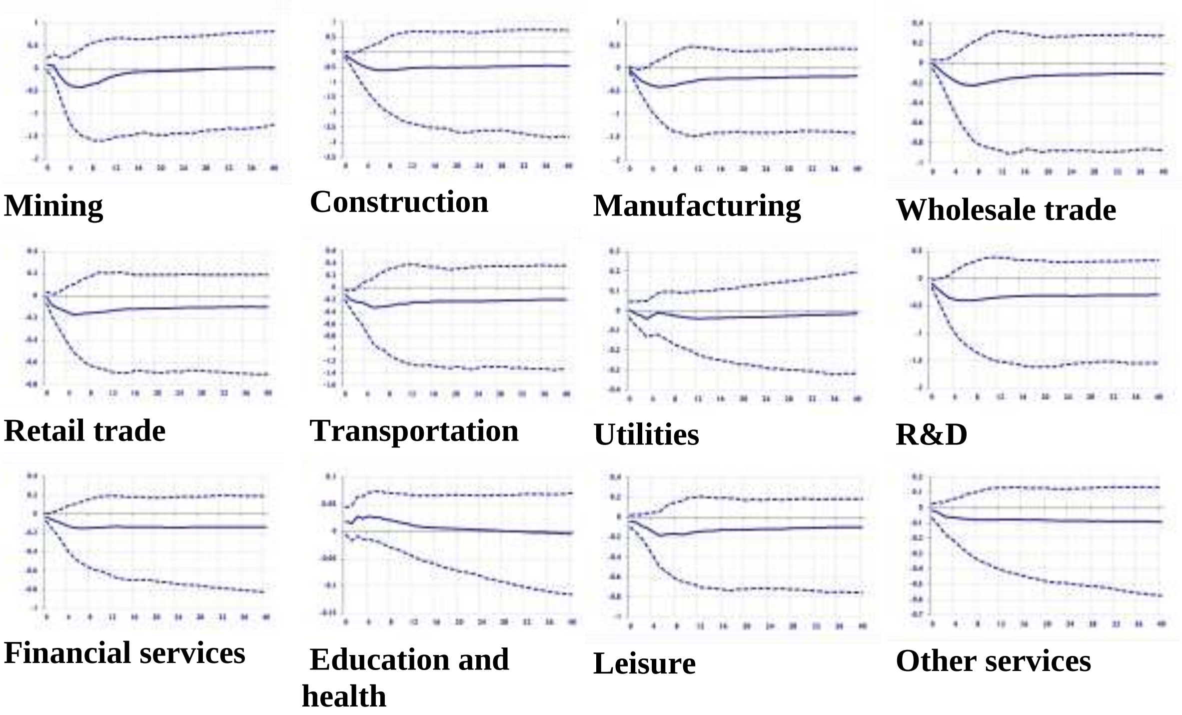
Investment-specific technology shock



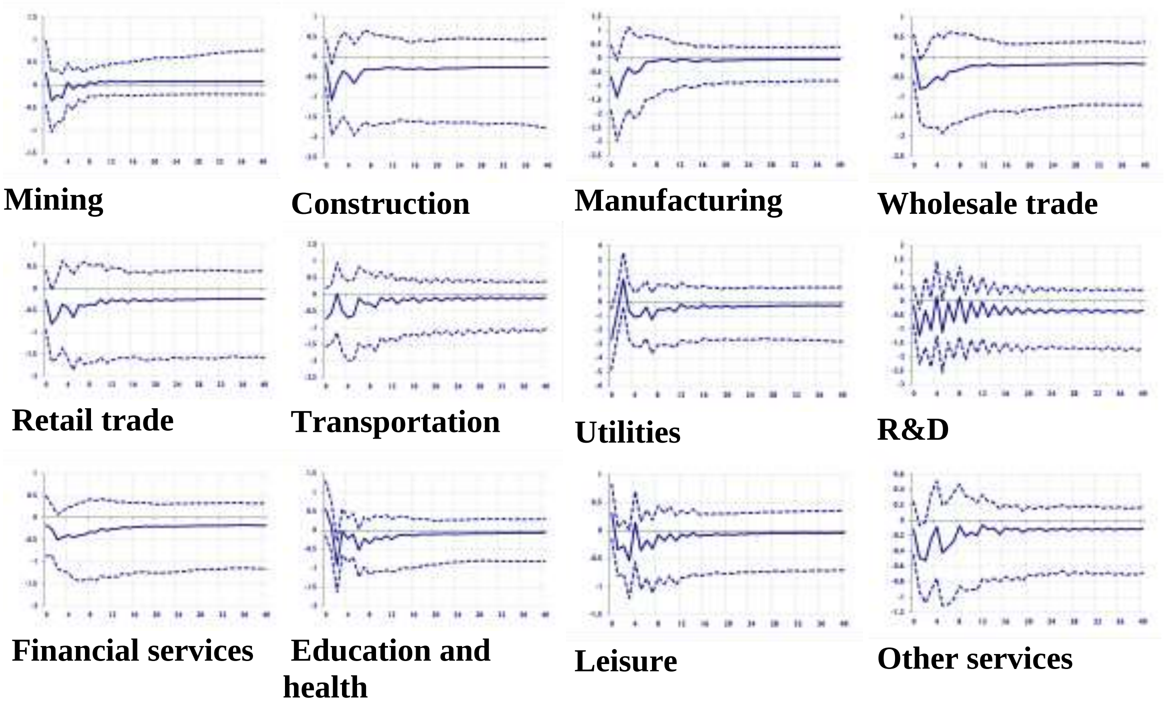
Note. All sectors are aggregated using sector-specific averages

Figure 2. Generalized Impulse Response Functions (GIRFs) to a positive one std. neutral-technology shock. Baseline specification.

Panel A. Median responses and 90% confidence bands for E (employment)



Panel B. Median responses and 90% confidence bands for C (creation)



Panel C. Median responses for E (employment – dotted line), C (creation – blue line) and computed D (destruction – red line)

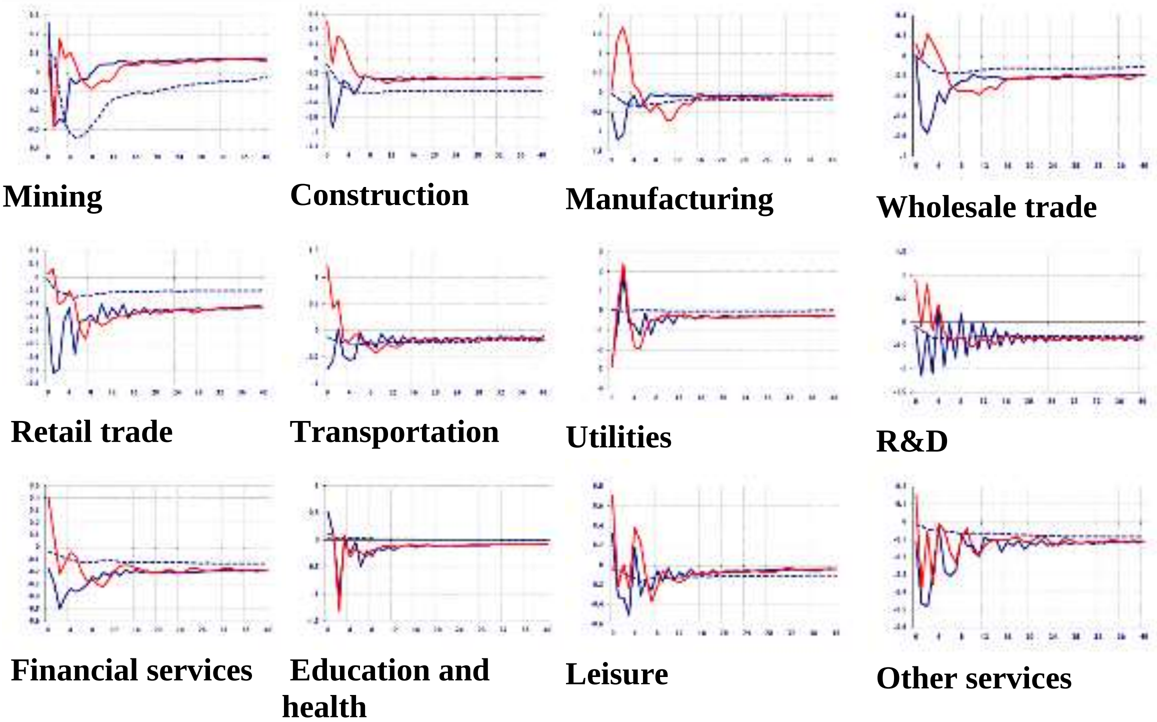
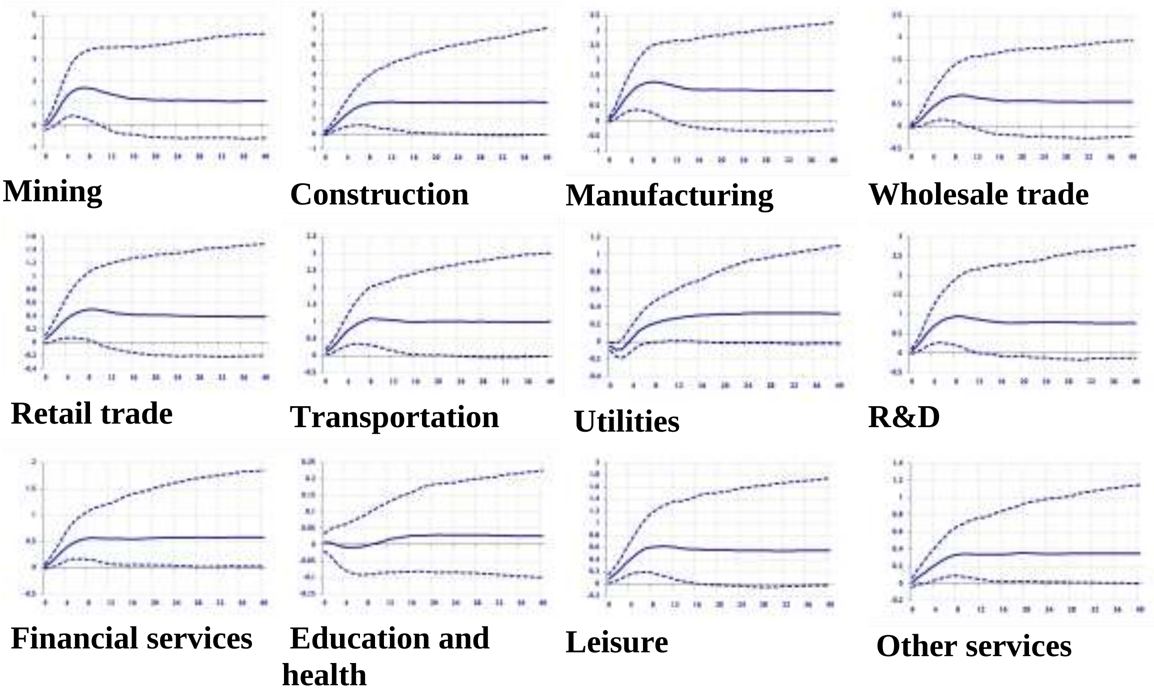
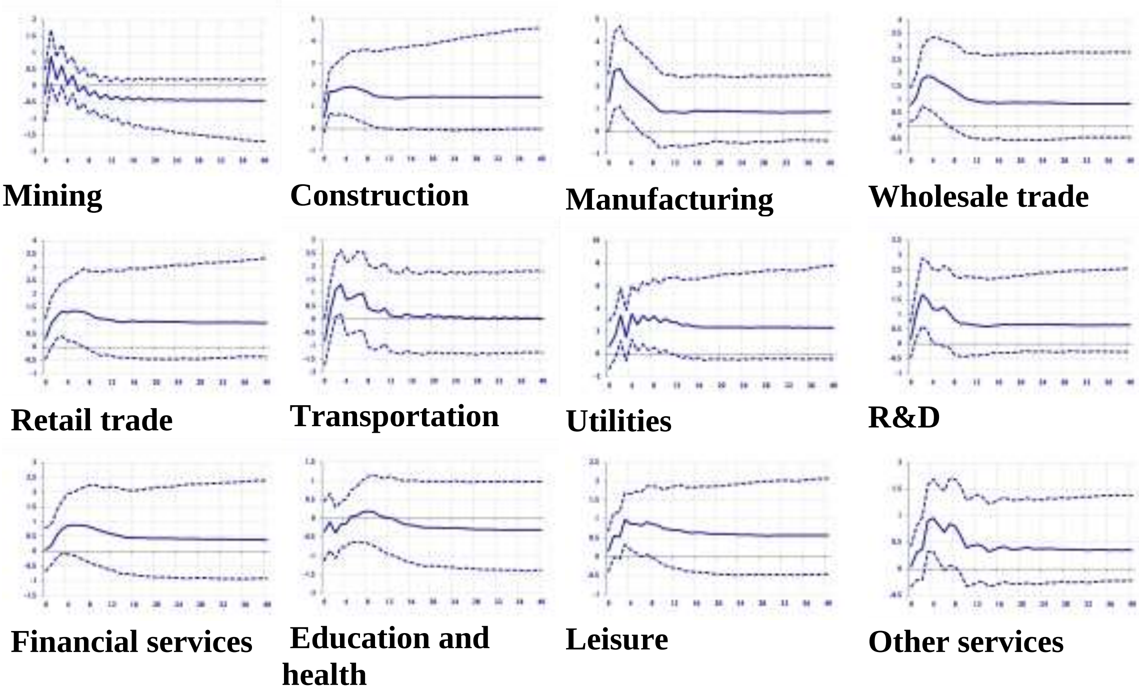


Figure 3. Generalized Impulse Response Functions (GIRFs) to a positive one std. investment-specific technology shock. Baseline specification.

Panel A. Median responses and 90% confidence bands for E (employment)



Panel B. Median responses and 90% confidence bands for C (creation)



Panel C. Median responses for E (employment – dotted line), C (creation – blue line) and computed D (destruction – red line)

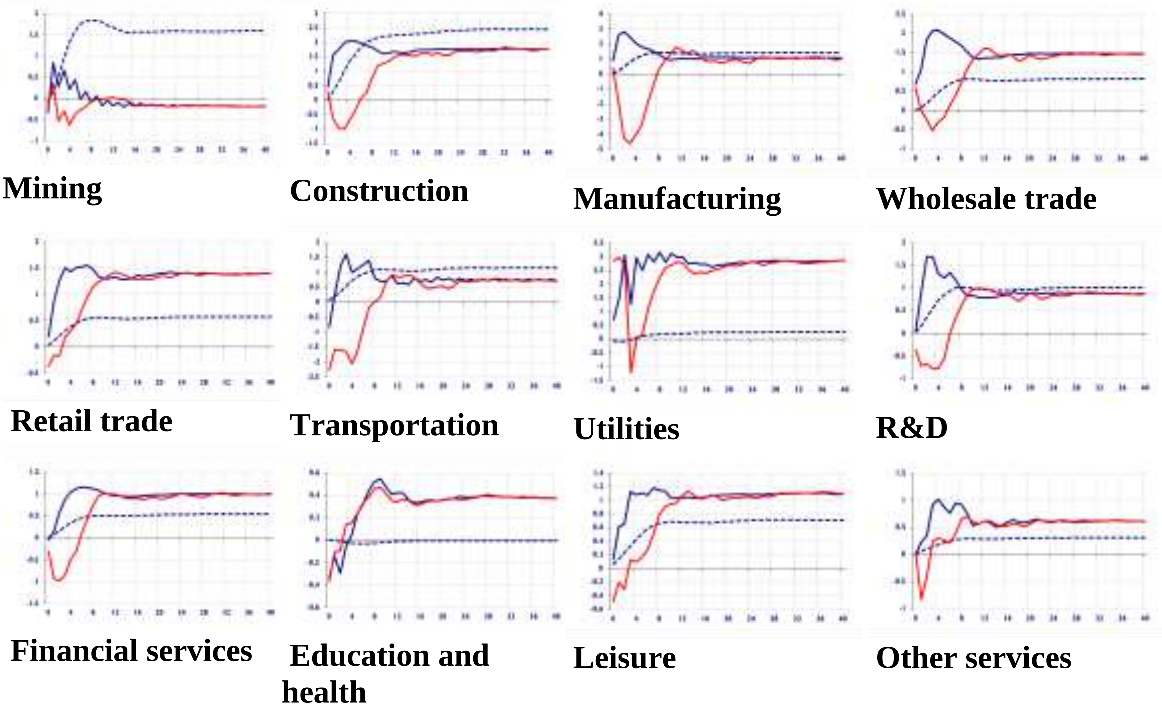
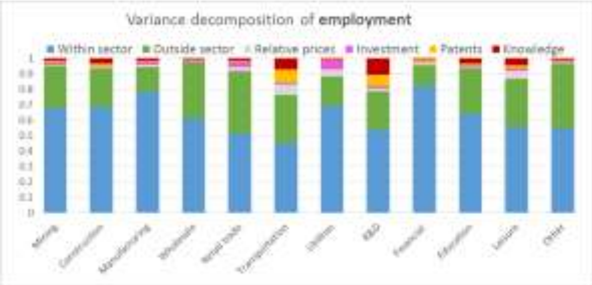
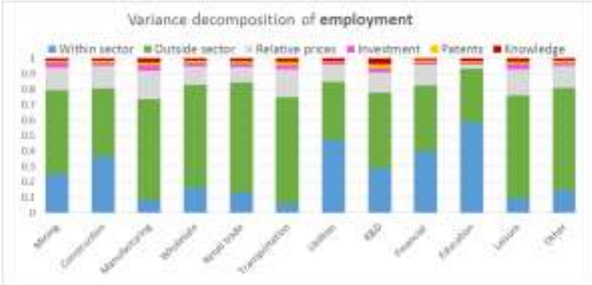


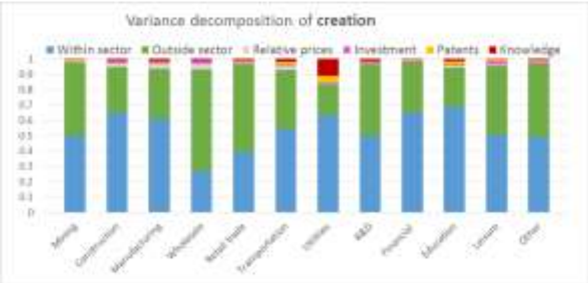
Figure 4. Generalized forecast error variance decomposition - GFEVD

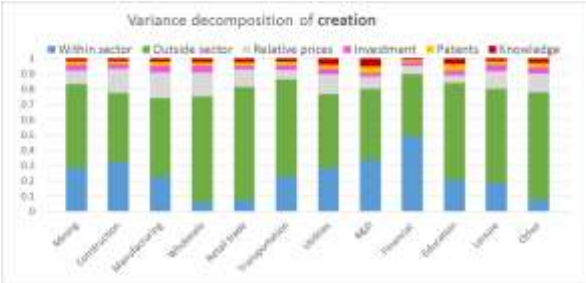




At impact (T0)

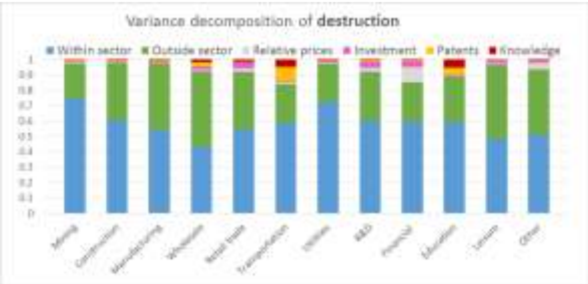
After 20 quarters (T20)

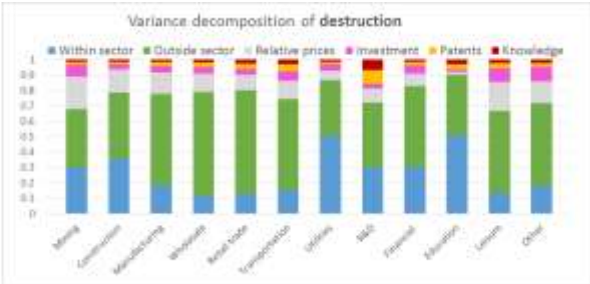




At impact (T0)

After 20 quarters (T20)





At impact (T0)

After 20 quarters (T20)

Note: The variance decompositions presented on the first and second row are derived using the baseline model specification, where employment and creation are endogenous variables. The variance decompositions in the third (last) row are based on the alternative model specification, with employment and destructions as endogenous.