UNIVERSITÀ DI SIENA 1240

QUADERNI DEL DIPARTIMENTO DI ECONOMIA POLITICA E STATISTICA

Marwil J. Dávila-Fernández

Manufacture Content and Financialisation: An Empirical Assessment

n. 811 – Ottobre 2019

Manufacture content and Financialisation: an empirical assessment*

Marwil J. Dávila-Fernández

University of Siena

October, 2019

Abstract

Over the past fifty years, the United States (US) has experienced a process of structural change characterised by an increase in financial and a decrease in manufacture technical coefficients. In this article, we argue that both processes are intrinsically related. Building on Dávila-Fernández and Punzo (2019) *multisectoral approach to financialisation*, technical coefficients can be understood as measures of input content per unit of output produced. Using a 15-sector level of aggregation, we revisit the evolution of manufacture content in the US between 1947 and 2015. We proceed by applying time-series cointegration techniques and dynamic panel estimation methods to assess the correspondence between different measures of manufacture and financial content. Our results indicate that there is a negative long-run relationship between both series with financialisation being weakly exogenous and having predictive power over manufacture content. We conclude discussing the role of financial liberalisation, shareholder value orientation, and firm indebtedness to explain how a more financial intensive production technique has displaced manufacture inputs.

Keywords: Financialisation, Deindustrialisation, Input-Output, Cointegration, United States.

JEL: E12; E32; O40;

*An earlier version of this article was presented at the Analytical Political Economy Workshop, University of Massachusetts, United States. We are grateful to the participants and in particular to Peter Skott, Raphael Gouvea, and Daniele Girardi for helpful comments and suggestions. The usual caveats apply.

1 Introduction

Structural change is a term that has been used loosely in the economic literature depending on the issue being studied. Even though a precise concept varies across analysis, the shared premise is of a shift or change in the basic ways the economic system functions. It involves the study of changes in the sectoral configuration of the economy, aspects of international economic integration, the effects of the incorporation of new technologies, etc.

In recent decades, advanced countries have undertaken a process of industrial transformation and structural change characterised by an increasing importance of service sectors and a declining weight of manufacturing activities (Peneder et al, 2003; Castellacci, 2010; Montresor and Marzetti, 2010). The rise of services may be considered one o the main characteristics of the so called "knowledge economy" (Ciriaci and Palma, 2016, p. 55). Although it dates back to early 1940s, the hypothesis that economic development passes through a binomial deindustrialisation-tertiarisation has reemerged in recent debate. It does not take much to see this relationship. If the relative importance of primary activities such as agriculture or mining remains constant over time, an eventual rise of services must be followed by a decline in manufacture.

A popular and effective way of investigating structural change is making use of the input-output (IO) framework because it is a unique and rich representation of the economic structure. The use of IO techniques in the analysis of structural change is as old as the discipline itself and goes back to Leontief (1941) and Chenery (1960). In this respect, "the analysis of economic change by means of a set of comparative static changes in key parameters in an input-output table" (Rose and Chen, 1991, p. 3), or Structural Decomposition Analysis (SDA), has consolidated itself over the past years as a powerful tool for distinguishing major sources of change in the economy.

Among service activities, one in particular has received perhaps limited attention in the IO/SDA literature despite its importance for the functioning of the entire economic system, namely, the financial sector.[1] An increase in relative importance of the financial side of the economy has been the subject of a large body of scholarship inside and outside social sciences. Frequently referred to as *financialisation*, this literature has documented with some success the "increasing role of financial motives, financial markets, financial actors and financial institutions in the operations of the domestic and international economies" (Epstein, 2005, p. 3).

It is possible to differentiate, for expositional purposes, between three main approaches to financialisation (see van der Zwan, 2014). There is a long tradition mainly concerned with what is produced in the economy from a long-run perspective. In this case, financialisation is seen as a regime of accumulation in which "profits accrue primarily through financial channels rather than through trade and commodity production"(Krippner, 2005, p. 174). A second approach has examined the role of shareholder value orientation as a guiding principle of corporate behaviour. Finally, a third group of scholars have adopted a cultural perspective, emphasising the encroachment of finance into the realms of everyday life.

One should notice, however, that methods focusing on sectoral disaggregation have also received limited attention in the financialisation literature. In a very recent contribution, Dávila-Fernández and Punzo (2019, DF&P hereafter) have proposed an innovative multisectoral approach to study this phenomenon. Financialisation is understood as *an increase in*

[1] Two remarkable exceptions are Leung and Secrieru (2012) and Aray et al (2017). For recent applications of SDA, see Toh and Thangavelu (2013) and Incera (2017).

financial content in monetary terms of each unit of output produced. Financial content is measured through the matrix of technical coefficients and the well known Leontief inverse matrix. Following the SDA literature, their analysis is based on the identification of changes in technical coefficients across sectors in the IO tables. An application to the United States (US), between 1947 and 2015, pointed out to significant increases in financial content, especially in the service sector.

Taking DF&P as the starting point of our analysis, we see the rise of the financial sector as a change in the production technique that brings an increase of financial content in production. Throughout this article, by financial sector, we mean financial intermediation, insurance, real estate, rental and leasing, forming the FIRE acronym. Measures of direct and indirect content are technical coefficients, and as such, reflect the technology available and used at a certain moment. An increase in financial content means that the respective production technique is using more intensively financial inputs. Such an increase is what we refer to as financialisation.[2]

On the other hand, when it comes to manufacture activities, several studies have reported a reduction in the respective technical coefficients indicating that, for developed countries, manufacture content has been declining over time (e.g. Feldman et al, 1987; Driver, 1994; Peneder et al, 2003; Franke and Kalmbach, 2005; Savona and Lorentz, 2006). This reduction is at the core of recent contributions that study deindustrialisation and tertiarisation using the IO framework (e.g. Montresor and Marzetti, 2011; Ciriaci and Palma, 2016; Peneder and Streicher, 2017). Extending DF&P main insight to the manufacture sector, a reduction in manufacture content per unit of output could be seem as a footprint of deindustrialisation itself.

It is not our intention to put forward a new conceptualisation of deindustrialisation. Still, we wonder what could explain the decrease in manufacture technical coefficients. The OECD, for instance, has recently indicated that changes in IO linkages explain a sizeable share of the manufacture relative decline in developed countries, being more important than changes in tastes or trade (OECD Economic Outlook, 2017). In this article, we argue that the observed increase in financial content and the reduction in manufacture content are two related phenomenon. It is our purpose to investigate the nature of this correspondence.

Using a 15-sector level of aggregation, we revisit the evolution of manufacture technical coefficients in the United States between 1947 and 2015. Nine sectors presented a continuous reduction in manufacture content while thirteen exhibited a similar negative trend over the past thirty years. We proceed by applying time-series cointegration techniques to study the correspondence between different aggregate measures of manufacture and financial content.

Three models are estimated, namely, a Vector Error Correction (VEC), a Fully Modified Ordinary Least Squares (FMOLS), and a Dynamic Ordinary Least Squares (DOLS). It is shown that there is a negative long-run relationship between both series such that, in our preferred scenario, an increase of one unit of the financial technical coefficient is associated with a reduction of two units in the manufacture coefficient. Moreover, Granger causality tests indicate that causality goes from financialisation to manufacture content. Our estimates suggest that financialisation is weakly exogenous and has predictive power over manufacture content.

[2] The concept of financialisation is particularly controversial, as it has been defined in various ways that often look mutually inconsistent. The main disadvantage of using IO tables in our endeavour is that we neglect from the start financial flows that are not linked to production (see, for example, Bezemer, 2016). Still, they allow us to explore an important dimension of the phenomenon that has not been properly discussed.

Finally, building on Autoregressive Distributed Lag (ARDL) modelling, Pooled Mean-Group (PMG) estimation methods are used to confront disaggregated series in a heterogeneous panel. Our estimates support the hypothesis that there is a long-run relationship between both series. Panel regressions show that an increase of one unit of direct financial content decreases direct manufacture content in $0.4 - 0.6$ units. Furthermore, panel Granger causality tests confirm our previous findings, suggesting that financialisation predicts the decline in manufacture content.

The remaining of the paper is organised as follows. In the next section, we present the sectoral evolution of manufacture content for the US economy providing some motivation to the relationship we are about to study. Section 3 brings our cointegration exercise using single aggregate measures for manufacture and financial technical coefficients. In the next section, we present our estimates of the heterogeneous panel ARDL based analysis. The economic rationality of our main findings is discussed in Section 5. Some final considerations follow.

2 Assessing manufacture content

If the relative importance of primary activities such as agriculture or mining remains constant over time, an eventual rise of services must be followed by a decline in manufacture. In that sense, deindustrialisation and tertiarisation can be understood as different sides of the same phenomenon. Different explanations are found in the literature for the dynamics behind this relationship that in general point out to the role of outsourcing, changes in relative prices, Bell's Law, productivity gains, etc (e.g. Rowthorn and Coutts, 2004; Palma, 2008). Still, those explanations do not refer specifically to how the financial sector might enter the story.

A possible way to do it and that will be further discuss in Section 5 is the following. In an increasingly integrated world economy, international competition between firms has increased as global markets expanded and integrated after World War II. Competition has forced firms to operate in a state of constant innovation and flexibility.[3] To keep profit margins, they have pursued either product differentiation − with the creation of new goods, branches and markets − and/or cost reductions − moving production abroad to low-wage countries.

In the first case, there has been a systematic reallocation of jobs and value-added towards high-skill intensive service sectors. This movement has been labelled by some authors as "Skill Biased Structural Change"(Buera and Kaboski, 2012; Buera et al, 2015). The alternative has resulted in moving production abroad to low-wage countries. Firms in the search of lower labour costs and/or more lenient tax systems have invested abroad. There is a mix of integration in trade with disintegration of production that has been well documented in the growing literature on global value chains (Gereffi et al, 2005; Seabrooke and Wigan, 2017). In the United States, this process has resulted in the increase of the non-manufacture share on employment.

Furthermore, globalisation has favoured the development of new financial instruments, encouraging firms to narrow their scope to core competence. In this context, the liberalisation of international markets has provided incentives to fusions and acquisitions, while shareholder value orientation has contributed to increase the pressure for profitability (Milberg, 2008; Milberg and Winkler, 2010; Brennan, 2016). Those last elements can be seem as catalysts for

[3]While the literature on innovation provides some evidence of an inverted-U relationship between competition and innovation, turning points only occur for elevated levels of the former (Aghion et al,2005; Aghion et al 2014). This means that most of the time competition is positive correlated with innovation.

deindustrialisation and provide a preliminary insight of the link between increases in relative importance of the financial sector, or financialisation, and the fall of manufacture activities.

For the purposes of this paper it might be useful to emphasise the meaning of direct technical coefficients. Suppose, as an example, that sector j used \$350 of goods from sector i to produce \$1000 of sector j's output. Hence, direct content (or the technical coefficient) of i in j is $350/1000 = 0.35$. In terms of financial content, if sector j uses \$50 of financial inputs to deliver \$1000 of its output, we say financial direct content in that sector is $50/1000 = 0.05$. When it comes to the manufacture sector, one could think of deindustrialisation not only as a reduction of the share of manufacture in employment and Gross Domestic Product (GDP) but also as a particular type of structural change that involves a reduction in manufacture content of each unit of output produced.[4]

In order to assess the nature of the relationship between financial and manufacture content, we refer specifically to direct technical coefficients. This does not mean that indirect effects are not important and/or cannot be studied. However, to assess econometrically the relationship between indirect coefficients is of little use because, by construction, they are a function of the interactions of direct coefficients of all industries. On the other hand, if we find a causal long-run correspondence between direct technical coefficients, this indicates that both processes of structural change are interconnected.

2.1 A note on data distortions

At this point we must make some important clarifications. In the beginning of this section, we mentioned that deindustrialisation implies tertiarisation and vice versa. At first, a similar situation could appear here since, for a given sector, the sum of technical coefficients plus the share of its value-added on total output must be equal to one. Nonetheless, we consider that there are important differences when it comes to financial and manufacture content because technical coefficients of different sectors move in different directions over time. Therefore, it is not obvious to us that an increase in one coefficient must be related to a decline in the other. We will come back to this point in Section 3.

Furthermore, as discussed in DF&P, several authors have shown that there might be important distortions in the way financial value-added is measured in national accounts (e.g. Basu and Foley, 2013; Assa, 2016). Such distortions could potentially bias our analysis and invalidate our exercise. For instance, it is possible to show that the overestimation of financial value-added introduces a negative bias on financial content. In what concerns manufacture content, a positive trend bias in how we measure financial GDP also has major implications. Obviously, one could disagree about the relevance of this critique to national accounts. Still, we speculate how different manufacture content trajectories would be if we give a different treatment to financial value-added.

Motivated by the treatment provided by DF&P, we calculate a second measure of manufacture and financial content, assuming all FIRE incomes as intermediate inputs to the rest of the economy. Such manipulation allows us to provide a more robust analysis, especially in terms of data trends. We redistribute financial value-added − as reported in the System of National Accounts (SNA) − so that it enters the IO table exclusively as inputs. This modified set-up corresponds to an extreme scenario that complements our analysis in two

[4] Deindustrialisation is traditionally defined as a decline in manufacturing as a share of total employment. However, some authors have advocate for the use of other measures such as manufacturing as a share of total output. For a broader discussion on those issues, see for example, Palma (2008) and Treggena (2009).

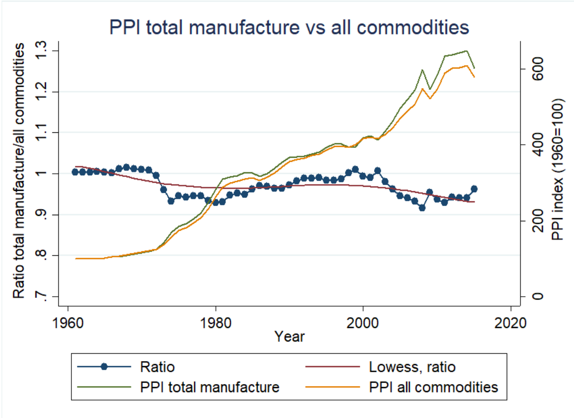

Figure 1: PPI total manufacture and all commodities

ways. From a descriptive point of view it basically shows if, in the limit, distortions change our main trends of interest. It also provides a second set of indicators that can be use to test the robustness of our econometric estimations. A formal assessment of how our alternative measures are constructed appears in the Mathematical Appendix.

Continuing, given that our analysis is performed using input-output tables at current prices, one could argue that we might be just capturing price dynamics. For example, the trends for manufacture value-added as a share of GDP are very different at current and constant prices. In the first case, there is a marked negative trajectory, meanwhile, at constant prices, there is no trend at all (see, for example, Rodrik, 2016).

The problem is that the Bureau of Economic Analysis (BEA) publishes IO tables at current Production Prices (PPI) while the Bureau of Labor Statistics (BLS), responsible for producing price indexes, does not report deflators for all IO sectors. Still, we have reasons to believe that this does not compromises our analysis. For instance, the BLS publishes separate PPI indicators for total manufacture and for all commodities. There is not much difference between them, as we can see in Fig. 1. On the left, we have the ratio between the two indexes while, on the right, we have actual PPIs. There is no particular trend indicating that prices in manufacture have behaved very differently that in other sectors. Therefore, we proceed describing our database and some main trends before performing our main econometric exercise.

2.2 Data and descriptive statistics

Our database takes a 15-sector level of aggregation for the US and comprehends the period 1947-2015. Data is in monetary terms and was provided by the Bureau of Economic Analysis (BEA). The Industry Economic Accounts (IEA) of the BEA are available at three levels of detail: sector (15 industry groups), summary (71 industry groups), and detail (389 industry groups). We chose to use a 15-sector level of aggregation because it allows us to address sectoral differences keeping the analysis as simple as possible. Time span was chosen given data availability.

Fig. 2 reports the evolution of manufacture direct content per sector. The most important feature is the clear general tendency of a reduction in manufacture technical coefficients.

Nine out of fifteen sectors presented an almost continuous contraction in direct content for the whole sample. On the other hand, "Agriculture", "Manufacture", "Wholesale", and "Education and Health" experienced inverted-U trajectories with the peak around 1970 and 1980. Overall, thirteen out of fifteen sectors experienced a reduction in manufacture direct content in the last thirty years. Such trends are in line with the financialisation literature that indicates the eighties as a decade with important transformations in the way the economic system operates.

We document expressive reductions in manufacture content, with coefficients diminishing in a range from $40 - 75\%$. The two exceptions are "Government", and "Transportation and warehousing". The first one presented a stable trajectory with no trend. Nonetheless, the latter follows a unique increasing path briefly reverted in the 1980s but resumed in the next decade until the end of the series. Finally, notice that there is no much difference between our preferred and modified measures of manufacture content, both in terms of levels and trends.

A similar negative trend appears when we aggregate data using the shares of each sector in total output. Fig. 3, on the left, depicts aggregate manufacture direct content per unit of output while, on the right, we have financial direct content. One could debate if the manufacture technical coefficient presented a negative trend between 1950 and 1970. Still, after 1970, it was strongly reduced from 0.2 to around 0.12 in 2015. Moreover, notice that our preferred indicator and our modified measure display similar trajectories, both in terms of trends and levels.

Financial content, on the other hand, depicts a positive trajectory for the whole sample. In our preferred scenario, there is a small increase until 1980 followed by an upswing in the slope of the curve. Redistributing FIRE's value-added as intermediary inputs brings a continuous increase in financial content from 1950 to the financial crisis in 2007. That is, trends are similar though there are important differences in terms of levels.

Aggregate measures embody two different movements in data. The first one concerns changes in coefficients. The second refers to the share of manufacture and financial industries in total output. In fact, manufacturing share in total output depicts a negative trend for the whole sample going from 40% to less than 20%. This, of course, contrasts with changes observed in the financial sector. Financial share in total output went to the opposite direction, increasing from 8% to 18%, as we can see in Fig. 4. We refer to this as a composition problem and we shall come back to it in Section 4.

With these results in mind we perform in the next section a cointegration exercise to assess the long-run relationship between financialisation and the reduction of manufacture content. In the last section, we move on to a disaggregate framework.

3 A cointegration exercise

To ascertain the existence of a long-run relationship between financialisation and changes in manufacture content, we make use of time-series cointegration techniques. At this stage, our exercise is constrained to an aggregate set-up. In the next section, we proceed by extending it to a heterogeneous panel. Our strategy consists in estimating two basic models, testing the robustness of our results to different estimators. In model 1, we confront our preferred measure of financial and manufacture direct content while, in model 2, we repeat the exercise for the case in which financial value-added was redistributed as intermediary inputs.

In order to test if variables are stationary, we performed the standard Augmented Dickey-Fuller (ADF) test, the Dickey-Fuller test with GLS detrending (DF-GLS), and the DF unit

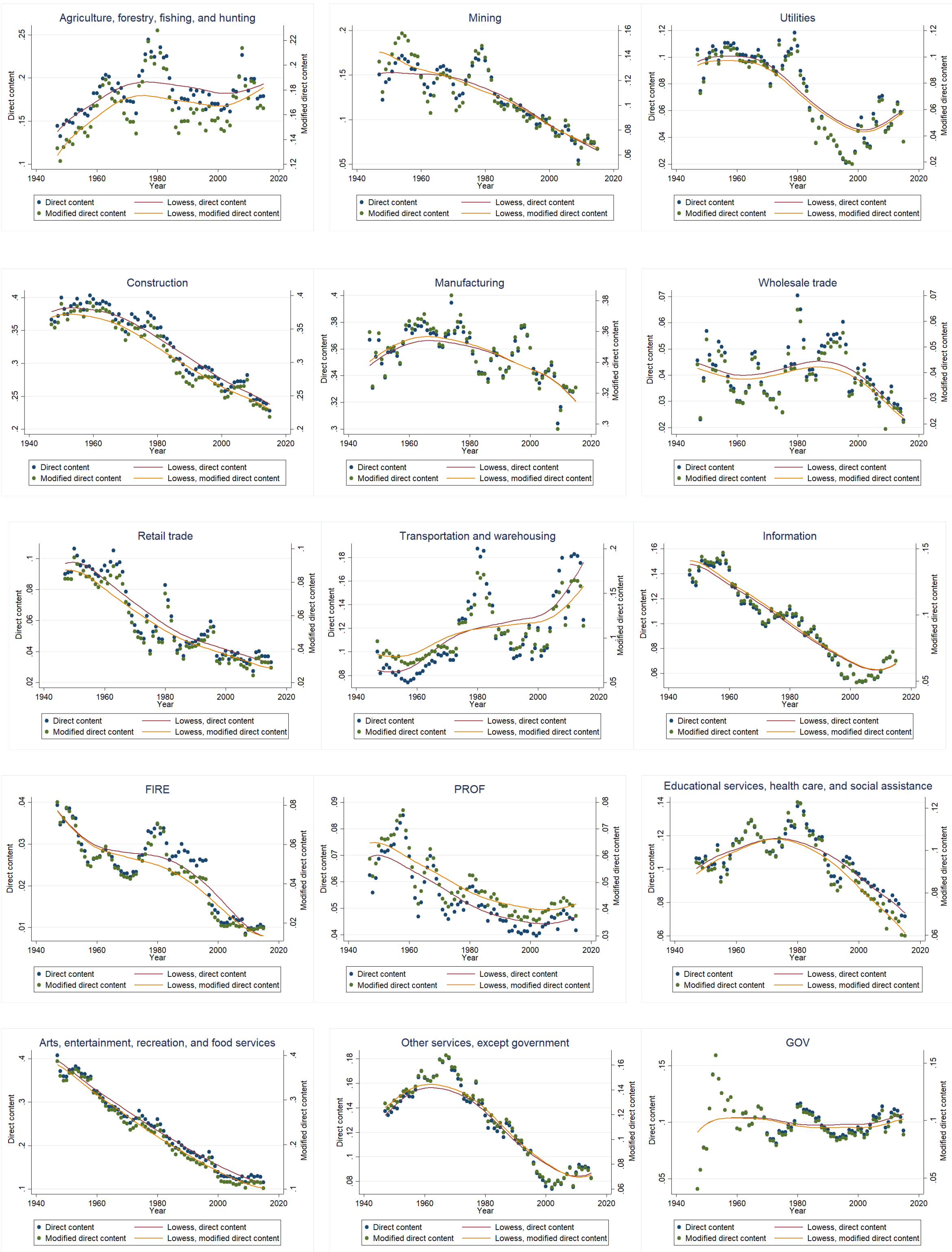

Figure 2: Manufacture direct content

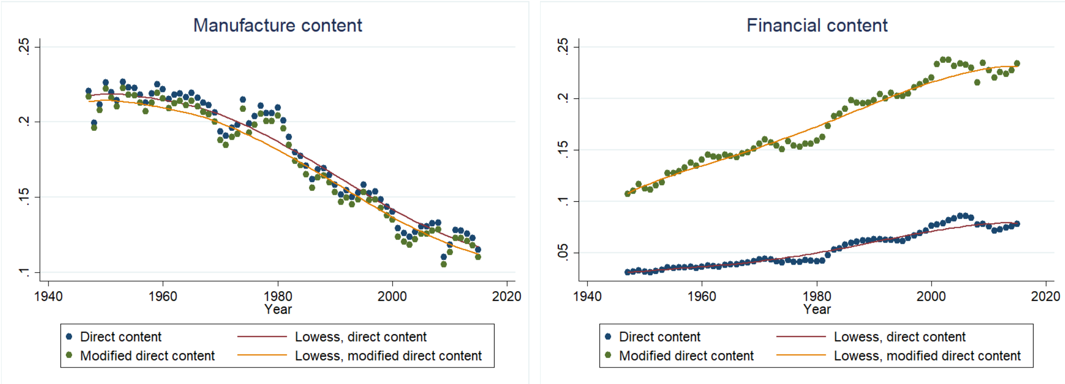

Figure 3: Aggregate manufacture and FIRE direct content

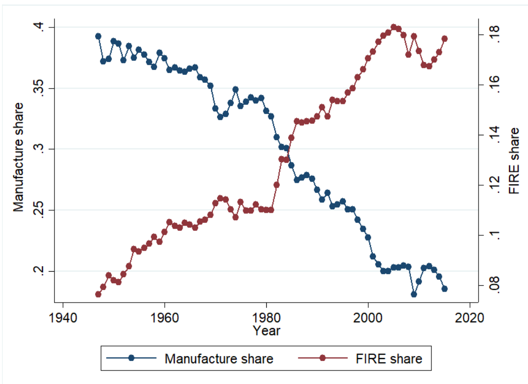

Figure 4: Manufacture and FIRE output shares

root test with a break-point. Results are reported in the Empirical Appendix and indicate that series are integrated of order one (see tables A1 to A4). Once we identify that our data is I(1), we apply the Johansen cointegration test.

We follow closely the methodology proposed by Risso et al (2013), which requires estimating a VEC model. From visual inspection, we identified a structural break around the 1980s. Multiple break point Bai-Perron test identifies several breaks for direct financial content (1957, 1967, 1983, 1996, 2006 in our preferred set-up; 1958, 1969, 1983, 1998 in our modified case) and direct manufacture content (1957, 1969, 1982, 1992, 2002 in our main scenario; 1969, 1985, 2000 in the second case). Therefore, all models estimated in this section include dummy variables to capture the structural break effects. One dummy variable was assigned for each indicator. They assume value 1 for years with breaks and zero for years with no break.

Schwarz's Bayesian Information Criteria (SBIC) was used for choosing lag selection. We allow for automatic lag selection imposing a maximum of 4 lags. SBIC criterion was preferred over the popular Akaike (AIC) insofar as it is strongly consistent while AIC is generally more efficient though not consistent. In other words, while the former will asymptotically deliver the correct model order, the latter will deliver on average a too large model (Brooks, 2014). Still, whenever serial correlation was potentially harmful, we opted for using AIC given that it assigns a higher number of lags, thus, controlling for serial correlation problems.

Table 1 reports results of the Johansen cointegration test identifying at least one cointegration relation between financial and manufacturing coefficients. This result is robust to the inclusion of data trends for both trace and maximum eigenvalue statistics. In Table 2, we present the long-run cointegration equation and the short-run coefficients of the VEC model. Notice that all error correction terms are negative so that there is convergence to the long-run solution. Moreover, the cointegration equation term of financial content is not statistically significant, which implies that this variable is weakly exogenous. Under weak exogeneity, we are allowed to carry out optimal inference with respect to the set of parameters of the long run equation (see Johansen, 1995). This means that we can take the parameters of the long-run equation without the necessity of modelling the endogenous dynamics of financial content.

Table 1: Number of cointegrating relations by model

Model 1: VEC(1,1)				
Data trend	None	Linear	Linear	Quadratic
Test type	Intercept/No trend	Intercept/No trend	Interecept/Trend	Intercept/Trend
Trace	1	1	1	2
Max-Eig.	1	1	1	2
Model 2: VEC(1,1)				
Data trend	None	Linear	Linear	Quadratic
Test type	Intercept/No trend	Intercept/No trend	Intercept/Trend	Intercept/Trend
Trace	2	1	1	2
Max-Eig.	2	1	1	2

While it is true that deindustrialisation and tertiarisation can be understood as different sides of the same phenomenon, it is not obvious that increases in financial content must be related to a decrease in manufacture content. Given that we are dealing with a 15-sector level of aggregation, different sectors move in different directions over time. Nonetheless, one could still make the case that, other things being equal, an increase of one variable implies a reduction in the other. We refer to this as the "ceteris paribus" problem. Even in that case, the importance of our exercise is twofold. First, to estimate the magnitudes involved. Second, to indicate who is moving first, addressing in that way predictive causality.

If there is a long-run negative relationship driven mainly by the "ceteris paribus" effect, two outcomes are expected. On the one hand, estimated coefficients must be close to 1. On the other hand, we should obtain bi-direction causality. We show this is not the case. Over the long run, technical coefficients are negatively related but an increase of one unit in direct financial content is associated with a reduction between $1-2$ units of manufacture content, depending on the model specification. On the other hand, short-run coefficients are not significant, suggesting that in the short-run there is no relationship at all.

Table 2: Long and short-run coefficients in the VEC model

Long-run equation	Model 1: VEC(1,1)	Model 2: VEC(1,1)
Manuf. content	1.000000	1.000000
Finan. content	2.201808***	1.020812***
C	-0.297452	-0.353996

	Model 1: VEC(1,1)		Model 2: VEC(1,1)	
Short-run equation	D(Manuf. content)	D(Finan. content)	D(Manuf. content)	D(Finan. content)
Error correction	-0.344128***	-0.028802	-0.269091***	-0.003270
D(Manuf. content[-1])	0.039075	0.042233	0.109782	-0.170661
D(Finan. content[-1])	0.301695	0.395495***	0.355861	-0.335847**
C	-0.000999	0.000350	-0.001515*	0.001901***
Dummy Manuf.	-0.003083	0.000854	-0.001468	0.000998
Dummy Finan.	-0.002350	0.001060	-0.002883	0.004107
Adj. R^2	0.124848	0.089415	0.129373	0.022220

*, **, and *** stand by 10%, 5% and 1% of significance

In order to assess the robustness of this result, we rely on FMOLS and DOLS estimators. Both are single equation methods that deal with endogeneity problems and are asymptotically equivalent and efficient. The robustness of the cointegration relation is also verified using the Hansen cointegration instability test. In what concerns model 1, AIC criteria selected a prewhitening with two lags, for FMOLS, and zero lead and length, for the DOLS regressions. In model 2, we have a prewhitening with one lag, for FMOLS, while four lead and five length, for DOLS. In all cases, we allowed for automatic lag selection imposing a maximum of 4 lags and 10 leads/lags for FMOLS and DOLS, respectively. The Akaike criteria was preferred over the SBIC because it allowed additional lags, avoiding in this case serial correlation problems. Results are reported in Table 3.

An increase of one unit in direct financial content is associated with a decrease of around 2.1 units of manufacture content in the first scenario and a reduction of 0.9 units in the

Table 3: FMOLS and DOLS estimations

Dependent variable: Manuf. content				
	Model 1		Model 2	
Regressors	FMOLS(2)	DOLS(0,0)	FMOLS(1)	DOLS(4,5)
Finan. content	-2.135376***	-2.091596***	-0.907003***	-0.964934***
C	0.292828***	0.291094***	0.332351***	0.342516***
Dummy Manuf.	-0.003531	-0.002527	0.009759	0.000679
Dummy Finan.	0.005788	0.003740	-0.003140	-0.000723
Adj. R^2	0.949240	0.949676	0.934570	0.976590
Hansen (Lc statistic)	0.262471	0.023661	0.832700	0.015705
Cointegration	Yes	Yes	No	Yes

*, **, and *** stand by 10%, 5% and 1% of significance

second model. We cannot reject the null of cointegration in three out of four models. The magnitude of coefficients in the FMOLS and DOLS regressions is similar to the one obtained from the VEC regressions. Our estimates give support to the thesis of a negative long-run relationship between technical coefficients of the financial and manufacture sectors.

After establishing that series cointegrate, we proceed to determine the existence of causality. A first attempt to get an insight about the direction of causality is given by the weakly exogeneity test. However, exogeneity does not mean causality. When variables are I(1), Toda and Yamamoto (1995) one extra lag modification of the Granger test is advisable. Nevertheless, this method could be inefficient with small samples and there might be a loss of power due to an overspecification of the lag length. Moreover, when there is cointegration, the standard Wald test yields better results than a modified test estimating extra coefficients (see Dolado and Lütkepohl, 1996; Lütkepohl, 2005). Thus, the Toda and Yamamoto procedure is not always needed. In Table 4, we present results of VAR Granger causality based on the Wald test.

Table 4: VAR Granger Causality, Block exogeneity test

Dependent variable: Manuf. content				
	Model 1		Model 2	
Excluded	df	Prob.	df	Prob.
Finan. content	1	0.0048	1	0.0373

Dependent variable: Finan. content				
	Model 1		Model 2	
Excluded	df	Prob.	df	Prob
Manuf. content	1	0.7814	1	0.9654

Our exercise indicates that there is unilateral causality going from financial to manufacture technical coefficients in both scenarios. This allow us to claim that an increase of one unit of direct financial content – in monetary terms per unit of output produced – causes a decrease between one and two units in manufacture content. We find this result extremely important because shows that financial content is weakly exogenous and has predictive power over manufacture content. That is, changes go from the financial to the manufacture sector.

To assess a valid inference and not spurious regressions, residuals of all six regressions were checked for serial correlation. If residuals are correlated, the estimated coefficients would be biased and inconsistent. We conclude that our estimates are consistent, thus the cointegrating regressions are not spurious. Results are reported in the Empirical Appendix (see table A5 and A6).

4 A panel PMG/ARDL approach

It is quite common now to have panels in which both T – the number of time series observations – and N – the number of groups – are quite large. In the previous section, we were able to identify a negative long-run relationship between financial and manufacture technical coefficients with causality going from the financial sector to manufacture activities. However, we were confronting aggregate measures. In this section, we relax this assumption and build a panel in which for each one of the 15 sectors we have one technical coefficient for manufacturing and one for FIRE.

One may argue that the use of a panel set-up might not be appropriate for our task given the intrinsic specificities across productive sectors. Such specificities were quite clear, for example, when we revisited the evolution of manufacture technical coefficients. While there was a general negative trend, some activities presented an inverted-U trajectory and "Transportation and wharehousing" actually experienced an increase in manufacture content. There are also important differences in financial content trajectories among sectors, as reported by DF&P. In order to avoid this critique, we adopt heterogeneous panel techniques which allow us to take into account some of those issues.

Ascertaining the order of integration of the variables under analysis is an essential precondition to establish whether the use of panel cointegration tests is warranted. In this respect, we performed the Levin, Lin and Chu (LLC) test that assumes a common unit root process, and the Im, Pesaran and Shin (IPS), the ADF and the Phillips-Perron (PP) tests that assume individual unit root processes. Results are reported in the Empirical Appendix (tables A7 and A8). While we are able to establish that direct financial content is integrated of order one, we cannot determine if manufacture content is stationary in levels or if it is also I(1).

In this case, the use of MG and PMG estimators within an ARDL approach is useful since both provide consistent estimates in a dynamic panel context, even in the presence of potentially non-stationary regressors (Pesaran et al, 1999; Blackburne and Frank, 2007; Lanzafame, 2014).[5] The MG procedure consists in estimating N separate regressions and

[5]The asymptotics of large T dynamic panels are different from small T panels. The latter usually rely on fixed or random effects estimators or a combination of fixed effects and instrumental variable estimators such as the Generalised Method of Moments (GMM). However, these methods require the assumption of homogeneity of slope parameters that is often inappropriate when T is large (Blackburne and Frank, 2007). This point has been made by Pesaran and Smith (1995), and Im et al. (2003), among others. Moreover, for large T panels, nonstationarity is also a concern. MG and PMG estimators address both issues.

calculate the coefficient mean. On the other hand, the PMG estimator only allows short-run coefficients and error variances to differ across groups.

Given that PMG constrains long-run coefficients to be equal across panels, it yields efficient and consistent estimates only when the restrictions are true. However, if the true model is heterogeneous, estimates are inconsistent while the MG estimator is consistent in either case. The choice between MG and PMG depends on the trade-off between consistency and efficiency. Thus, a modified Hausman test on the long-run parameter homogeneity restriction can be used to choose the most appropriate model.

We allow for automatic lag selection imposing a maximum of 4 lags for dependent and independent variables. SBIC criteria chose an optimal ARDL(1,1). The calculated Hausman statistic is 1.1 for model 1 and 1.11 for model 2. Hence, we cannot reject the null hypothesis that differences in coefficients are not systematic, which means the PMG model is preferred. Results of the MG estimates and the Hausman test are reported in the Empirical Appendix (table A9). Table 5 brings our estimates of the PMG model.

Table 5: PMG/ARDL estimates

Long-run equation		
	Model 1: ARDL(1,1)	Model 2: ARDL(1,1)
Variable	Coefficient	Coefficient
Finan. content	-0.6672051***	-0.4145752***
Short-run equation		
	Model 1: ARDL(1,1)	Model 2: ARDL(1,1)
Variable	Coefficient	Coefficient
Coint. Equation	-.0869481***	-0.0798147***
D(Finan. content)	-0.216749	-0.1685292
C	0.0138741***	0.013748***

*, **, and *** stand by 10%, 5% and 1% of significance

An increase of one unit in direct financial content is related in the long-run to a decrease of $0.4 - 0.65$ units of manufacture content. One should notice that the magnitude of the effect is quite lower than previous estimates using aggregate data. An explanation for this is that changes in aggregate data actually also embody changes in the share of each sector in total output. In the last fifty years there has been a reduction in manufacture's share on output and an increase in service shares. This increases the apparent effect of financialisation obtained in Section 3.

A negative and significant error-correction term provides strong support for the hypothesis that the variables share a significant long-run relationship. Indeed, 8% of any movements into disequilibrium are corrected for within one period. However, when it comes to the short-run, financialisation seems to have no significant effect over manufacture content. An increase of one unit in financial direct content reduces manufacture technical coefficient in $0.15 - 0.2$ units though this magnitude is not statistically different from zero.

Since the PMG estimator allows short-run coefficients and error variances to differ across sectors, we present them, for model 1, in Table 6. This permits us to explain why in the previous table the financial short-run coefficient was not statistically significant. In the short-run, different sectors present very particular dynamics and it is not possible to identify a clear pattern. In seven sectors – "Utilities", "Retail trade", "Wholesale trade", "Information", "FIRE", "Education and Health", and "Other services" – an increase in financial direct content is actually associated with an increase in manufacture technical coefficient. This contrasts with the remaining eight sectors which present a negative relationship that in some cases is not statistically significant. Such heterogeneity emphasises the importance of analysis at a more disaggregated level and the relevance of our econometric choice.

Table 6: Sectoral short-run coefficients of PMG/ARDL estimates (Model 1)

Variable	Agriculture	Mining	Utilities
Coint. Equation	-0.1530733***	-0.0055911***	-0.0318887***
D(Finan. content)	-0.00196	-0.1625479***	0.4946509***
C	0.0344727***	-0.000268***	0.0019612***
Variable	Construction	Manufacturing	Retail trade
Coint. Equation	0.0088718***	-0.1664912***	-0.1414795***
D(Finan. content)	-0.5936278*	-1.895517	1.061522***
C	-0.0050037***	0.0606283***	0.0091342***
Variable	Wholesale trade	Transportation	Information
Coint. Equation	-0.0426033***	-0.0672731***	-0.022184***
D(Finan. content)	0.9339003***	-1.601407***	0.3202724***
C	0.0032862***	0.0119117***	0.0015708***
Variable	FIRE	PROF	Education and Health
Coint. Equation	-0.02097***	-0.0990279***	-0.2415257***
D(Finan. content)	0.026413***	-0.0659128*	0.3028954***
C	0.0021523***	0.0091326***	0.0384111***
Variable	Arts and Entertainment	Other services	GOV
Coint. Equation	-0.0362269***	-0.0212848***	-0.263474***
D(Finan. content)	-0.9271824***	0.1074204**	-0.1250154
C	0.0063219***	0.0028187***	0.0315809***

*, **, and *** stand by 10%, 5% and 1% of significance

These results do not change much if we look to short-run estimates of model 2. As we can see in Table 7, all coefficients become statistically significant at 5% but there is still sizable heterogeneity among sectors. "Agriculture", "Construction", "Manufacturing", "PROF", and "GOV"maintained their negative signal but became statistically significant. It is also worth noting that the only sector with a change in sign was "Other services".

As a final step, we investigate the existence of predictive causality using two different panel Granger tests. The first one treats the panel data as one large stacked set and assumes all coefficients are the same across all cross-sections. A second approach is to follow Dumitrescu-

Table 7: Sectoral short-run coefficients of PMG/ARDL estimates (Model 2)

Variable	Agriculture	Mining	Utilities
Coint. Equation	-0.149685***	-0.001465**	-0.028840***
D(Finan. content)	-0.069760***	-0.143610***	0.183763***
C	0.034269***	-0.000951***	0.001944***
Variable	Construction	Manufacturing	Retail trade
Coint. Equation	0.009310***	-0.165062***	-0.100648***
D(Finan. content)	-0.432521***	-1.004632***	0.435135***
C	-0.005059***	0.059647***	0.007674***
Variable	Wholesale trade	Transportation	Information
Coint. Equation	-0.033396***	-0.065522***	-0.024942***
D(Finan. content)	0.396660***	-0.773743***	0.107242***
C	0.003048***	0.012073***	0.002147***
Variable	FIRE	PROF	Education and Health
Coint. Equation	-0.008391***	-0.095425***	-0.215136***
D(Finan. content)	-0.121504***	-0.083872***	0.068455***
C	0.002045***	0.010391***	0.036954***
Variable	Arts and Entertainment	Other services	GOV
Coint. Equation	-0.035323***	-0.021801***	-0.260895***
D(Finan. content)	-0.502262***	-0.018888**	-0.568401***
C	0.006286***	0.003238***	0.032509***

*, **, and *** stand by 10%, 5% and 1% of significance

Hurlin (2012) and allow coefficients to be different over cross-sections. Since we are not able to determined precisely the order of integration of our series, we prefer to deal with them in first differences. Given that SBIC lag criteria chose an ARDL(1,1), our causality tests also allow for one lag. Table 8 brings our results.

We cannot reject the null of non-Granger causality going from manufacture to financial content. On the other hand, we do find causality from financial to manufacture technical coefficients. These outcomes are in line with what we discussed in the previous section showing that changes in financial direct content precede and have predictive power over what happens in the manufacture sector.

Once again, residuals were checked for serial correlation in order to assess valid inference and not spurious regressions. We concluded that our estimates are consistent. Results are reported in the Empirical Appendix (see table A10).

5 Discussion

Overall, the outcomes of our panel and time-series analysis bring qualified support to the hypothesis that financialisation, in the terms define by DF&P, is behind the reduction in

Table 8: Panel VAR Granger Causality

	Model 1				Model 2			
	Common coef.		Individual coef.		Common coef.		Individual coef.	
Dependent: Manuf. content	df	Prob.	df	Prob.	df	Prob.	df	Prob.
Excluded: Finan. content	1	0.0198	1	0.0101	1	0.0471	1	0.0212
	Common coef.		Individual coef.		Common coef.		Individual coef.	
Dependent: Finan. content	df	Prob.	df	Prob.	df	Prob.	df	Prob.
Excluded: Manuf. content	1	0.1380	1	0.1965	1	0.2386	1	0.1018

manufacture technical coefficients. From an IO perspective, what does it mean that an increase in financial content causes a reduction in manufacture content?

We started Section 2 telling a story that can be further examined now. Globalisation, understood as an increase in the level of integration of the world economy, might be behind the explanatory mechanism. A more integrated world economy increases competition between firms at an international level. In response to these pressures, corporations need to operate in a state of constant innovation and flexibility. To keep profit margins, they have been pushed to increase efficiency which can be seen, for instance, in the reduction of manufacture inputs used per unit of output produced, i.e. a reduction in manufacture technical coefficients.

Changes in the structural matrix have been described over the years as "technological change", often broadly interpreted to include any factor that causes a change in technical coefficients, such as true technological change, technical substitution as response to input price changes, and scale effects (Rose and Casler, 1996). We consider that understanding these changes as "efficiency gains" has some advantages especially when it comes to manufacture activities. The reason for this is that the literature on deindustrialisation has also documented an important process of service outsourcing that entails the so called tertiarisation effect (e.g. Montresor and Marzetti, 2010).

Outsourcing is usually conceived as a process that is symmetrical to vertical integration, reducing the vertical scope of the firm. In terms of structural change, it entails two movements. On the one hand, there is an artificial reduction in the economic contribution of manufacturing because the same activities are now recorded as services. On the other hand, it constitutes a particular kind of structural change amounting to an extension of the manufacturing into the non-manufacturing sectors. It involves the transfer of tacit and codified knowledge to the external organisation (McCarthya and Anagnostou, 2004) being an adaptation driven by transaction cost rewards.

The development of new financial instruments and shareholder value orientation have contributed to the maintenance of profitability, increasing the pressure for cost reductions and efficiency gains. If the increase in relative importance of the financial sector can effectively be captured by our measure of financial content, then it might help to explain why the increase in financial content is associated with a reduction of manufacture content. Such association is further in line with the idea of financialisation as a catalyst for deindustrialisation.

Moreover, while we could interpret the reduction in manufacture technical coefficients as an increase in efficiency in the use of those inputs, there are inefficiencies associated with a continuous increase in the need of financial inputs. Such observation reflects, in a sense, the fact that manufacture goods are tradable and therefore subject to international competition while FIRE is mainly a non-tradable.

Going deeper on what is behind these coefficients, notice that, to a great extend, financial inputs are a function of financial intermediation resulting in net interests income. Thus, changes in financial content are deeply related to the dynamics of interest rates and debt. This is in line with several interpretations of financialisation that put the increase in the volume of debt at the center of stage (see, for example, Palley, 2013). For instance, the strong increase of interest rates during the 1980s and of indebtedness afterwards has increased financial content. Such an increase has provoked a reduction in the use of other inputs because highly indebted firms cannot use freely inputs as before. As a result, the production technique is increasingly becoming more financial intensive, displacing manufacture inputs.

The idea that globalisation has brought an increase in competition is debatable. For instance, several scholars have pointed out a remarkably consistent upward trend in market concentration in the United States (e.g. Autor et al, 2017; Galston and Hendrickson, 2018). On the other hand, the reduction in multilateral and regional trade barriers, the fall in cost of international transport and communications, and the greater integration of capital markets have lead to higher levels of international competition (see, for example, Wiersema and Bowen, 2008; Mion and Zhu, 2013; Liu and Rosell, 2013; Bloom et al, 2016).

This apparent contradiction, however, might be just that, apparent. The key element is the complementarity between trade and technology. Higher foreign trade exposition may alter the return of different technologies. Data for a sample of European countries, for example, indicates that firms facing higher levels of Chinese import competition create more patents, raise their IT intensity, and increase their overall level of productivity (Bloom et al, 2016). Liu and Rosell (2013) also found for the United States that innovation is not neutral to the degree of international competition.

But then, why has industry sales concentration increased? Autor et al. (2017) hypothesise that industries are increasingly characterised by a "winner take most" feature so that superstar firms with higher productivity increasingly capture a larger slice of the market. If firms now are more likely to innovate and the persistence of firms' innovative advantage has risen, the innovator advantage would increase and so would its market share. Possible explanations for this process include the diffusion of new competitive on-line platforms (with high fixed or low-marginal costs) and rising international integration of product-financial markets. In that sense, one could speculate that the globalisation of markets has fundamentally changed competitive conditions. Low-tech firms have been negatively impacted while high-tech activities have flourished in a "winner take most" structure that has raised US market concentration.

In any case, in light of the results presented here, we understand that there has been a pressure for efficiency gains that is capture by a reduction in manufacture technical coefficients. Financialisation enters as a catalyst of this process. The production technique in the US is increasingly becoming more financial intensive, reducing manufacture content. Our story has several similarities with the aforementioned literature, though we emphasise the role of financial activities in an IO framework.

One should also keep in mind that we can referred to such negative relationship only in the long-run. In the short-term different sectors present different dynamics for both financial and manufacture content. It is perfectly possible that, for a certain sector, an increase in the financial technical coefficient is associated with an increase in the manufacture coefficient. This does not put into question our main argument, though it emphasises the importance of analysis also at a more disaggregated level.

In recent decades, advanced countries have undertaken a process of structural transformation characterised by an increase in importance of service sectors and a declining weight of manufacture. At least in what concerns the US, this phenomenon does not seems to be constrained to the labour market or GDP shares. A multi-sectoral approach to financialisation indicates that there is a negative long-run relationship between financialisation and the decline of manufacture content. Services and in particular the financial sector seem to be re-shaping economic fundamentals.

6 Final considerations

After the Second World War and especially in the last thirty five years, the United States has experienced a process of structural change characterised by an increase in financial content and a reduction in manufacture content per unit of output produced. In this article, we argued that both processes are related. Using a 15-sector level of aggregation, we studied the evolution of manufacture technical coefficients in the US between 1947 and 2015. To the best of our knowledge, we are the first to address finance and manufacture links looking directly to the evolution of sectoral technical coefficients. Our approach indicates that services and in particular the financial sector are indeed re-shaping economic fundamentals.

Nine sectors experienced a reduction in manufacture direct content for the whole sample while thirteen exhibited a similar negative trend in the last thirty years. These results can be reproduced if we aggregate the economy using the shares of each sector in total output. We proceed by applying cointegration techniques to the relation between single aggregate measures of manufacture and financial content. Finally, building on ARDL modeling, PMG estimation methods were used to confront disaggregated series in a heterogeneous panel. Overall results indicate that there is a negative long-run relationship between both series and that causality goes from financialisation to manufacture content. An increase of one unit in the financial sector technical coefficients is related to a decrease between 0.4 and 2 units of manufacture coefficients.

We make the case that financial liberalisation and shareholder value orientation have contributed to profitability, increasing the pressure for efficiency gains. Since both are part of a broader process referred to as financialisation, they could be part of the explanation of the aforementioned negative relationship. Furthermore, the increase in interest rates during the eighties and of indebtedness afterwards provides a mechanism linking increases in financial content to financialisation, with debt at the center of the stage. Given that highly indebt firms cannot use freely inputs as before, the production technique is becoming more financial intensive, displacing manufacture inputs. Our results join other recent efforts showing that financialisation and deindustrialisation processes might be intrinsically related.

Granger tests indicate that there is unilateral causality going from financial to manufacture technical coefficients. This allow us to claim that an increase of one unit of direct financial content causes a decrease between 0.4 and 2 units in manufacture content. We find this result extremely important since it implies that our conclusions are not driven mainly by the "ceteris paribus" problem. We actually have that *financial content is weakly exogenous, precedes and has predictive power over manufacture content.*

Table A1: Unit root tests (levels)

			Finan. content (t-statistic)	
Method	Intercept	Break year	Trend and intercept	Break year
ADF	-0.448705	-	-3.257610*	-
DF-GLS	0.557049	-	-2.085017	-
Breakpoint test	-3.822634	1981	-4.274469	1995
			Manuf. content (t-statistic)	
Method	Intercept	Break year	Trend and intercept	Break year
ADF	-0.271243	-	-2.897041	-
DF-GLS	0.492570	-	-2.447081	-
Breakpoint test	-3.002058	1980	-3.819164	1980

*, **, and *** stand by 10%, 5% and 1% of significance. SBIC automatic lag-length selection.

Empirical Appendix

Table A1 reports results of the unit root tests in levels for our main indicators of financial and manufacture direct content. Outcomes indicate that we cannot reject the null hypothesis that series are non-stationary in levels. In table A2, we repeat the same set of tests now for our modified financial and manufacture technical coefficients. Once more we have that it is not possible to reject the null of non-stationarity. Also notice that most Breakpoint tests indicate 1980 as break year. Table A3 presents results of unit root tests in first differences for our preferred scenario. We conclude series are integrated of order one. We proceed performing the same set of tests for our modified indicators now in first differences. The null of non-stationarity is rejected in all cases, as we can see in table A4.

Table A5 bring the results of the VEC Residual Serial Correlation LM Tests. We cannot reject the null hypothesis of no serial correlation, which indicates our VEC estimates are consistent. Stationarity of residuals of FMOLS and DOLS models are tested due to standard ADF unit root test. Results are reported in table A6. We conclude errors are stationary and, therefore, the cointegrating relations estimated are not spurious.

Table A7 reports outcomes of the panel unit root tests in levels of sectoral manufacture and financial content. The optimal number of lags was determined using the SBIC. In terms of our preferred indicators, financial content is non-stationary while results are not conclusive for manufacture content. Moving on to our modified set-up the situation is inverted. Manufacture content is clearly non-stationary but we cannot state precisely if this is also the case for financial content. Still, one can say for sure series are not integrated of order two. Table A8 brings the results of the panel unit root tests in first differences. Once more, the number of lags was chosen using the SBIC. Outcomes indicate that series are stationary in first differences, hence, they are at most I(1). This justifies our choice for the ARDL estimator.

MG estimates are presented in table A9. Notice that the long-run coefficient of financial content is not statistically significant neither in the basic or modified cases. Error correction terms are negative and significant as expected, showing that there is convergence to the long-run solution. However, Hausman test results give an statistic of 1.1 and 1.11 which justifies

Table A2: Unit root tests (levels)

	Mod. Finan. content (t-statistic)			
Method	Intercept	Break year	Trend and intercept	Break year
ADF	-0.936608	-	-2.403723	-
DF-GLS	1.121193	-	-2.463967	-
Breakpoint test	-3.134885	1981	-3.730143	1981
	Mod. Manuf. content (t-statistic)			
Method	Intercept	Break year	Trend and intercept	Break year
ADF	-0.312832	-	-2.936354	-
DF-GLS	0.498042	-	-2.535202	-
Breakpoint test	-3.014521	1980	-3.849367	1980

*, **, and *** stand by 10%, 5% and 1% of significance. SBIC automatic lag-length selection.

Table A3: Unit root tests (first differences)

	Finan. content (t-statistic)			
Method	Intercept	Break year	Trend and intercept	Break year
ADF	-5.680146***	-	-5.639946***	-
DF-GLS	-5.723793***	-	-5.708018***	-
Breakpoint test	-6.467647***	2008	-6.664748***	2008
	Manuf. content (t-statistic)			
Method	Intercept	Break year	Trend and intercept	Break year
ADF	-9.265483***	-	-9.387315***	-
DF-GLS	-1.701034*	-	-5.848057***	-
Breakpoint test	-10.00592***	1974	-9.936536***	2009

*, **, and *** stand by 10%, 5% and 1% of significance. SBIC automatic lag-length selection.

Table A4: Unit root tests (first differences)

	Mod. Finan. content (t-statistic)			
Method	Intercept	Break year	Trend and intercept	Break year
ADF	-9.231278***	-	-9.189571***	-
DF-GLS	-8.996576***	-	-9.231684***	-
Breakpoint test	-10.19717***	2008	-10.11312***	2008
	Mod. Manuf. content (t-statistic)			
Method	Intercept	Break year	Trend and intercept	Break year
ADF	-9.242496***	-	-9.340825***	-
DF-GLS	-1.699982*	-	-5.860066***	-
Breakpoint test	-9.950256	1974	-9.885815***	2009

*, **, and *** stand by 10%, 5% and 1% of significance. SBIC automatic lag-length selection.

Table A5: VEC residual serial correlation

H_0: No serial correlation at lag h		
	Model 1	Model 2
Lag	Prob.	Prob.
1	0.3567	0.8697
2	0.5217	0.6307
H_0: No serial correlation at lags 1 to h		
	Model 1	Model 2
Lag	Prob.	Prob.
1	0.3567	0.8697
2	0.3838	0.8165

Table A6: FMOLS and DOLS residuals unit root tests (levels)

	FMOLS, residuals (t-statistic)			
	Model 1		Model 2	
Method	Intercept	Trend and intercept	Intercept	Trend and intercept
ADF	-4.598494***	-4.559805***	-4.647814***	-4.767692***

	DOLS, residuals (t-statistic)			
	Model 1		Model 2	
Method	Intercept	Trend and intercept	Intercept	Trend and intercept
ADF	-4.391662***	-4.521170***	-3.877776***	-3.813678**

*, **, and *** stand by 10%, 5% and 1% of significance. SBIC automatic lag-length selection.

Table A7: Panel Unit root tests (levels)

	Manuf. content		Mod. Manuf. content	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
Method	Prob.	Prob.	Prob.	Prob.
Levin, Lin & Chu	0.2613	0.0109	0.8179	0.6321
Im, Pesaran and Shin	0.3844	0.0005	0.8470	0.5963
ADF	0.0993	0.0007	0.8419	0.7815
PP	0.1367	0.0159	0.6575	0.7719

	Finan. content		Mod. Finan. content	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
Method	Prob.	Prob.	Prob.	Prob.
Levin, Lin & Chu	0.9519	0.7424	0.7006	0.3342
Im, Pesaran and Shin	0.9894	0.6109	0.7494	0.0024
ADF	0.9910	0.6006	0.5928	0.0086
PP	0.9767	0.8331	0.1279	0.0108

Table 8: Panel Unit root tests (First difference)

	Manuf. content		Mod. Manuf. content	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
Method	Prob.	Prob.	Prob.	Prob.
Levin, Lin & Chu	0.0000	0.0000	0.0000	0.0000
Im, Pesaran and Shin	0.0000	0.0000	0.0000	0.0000
ADF	0.0000	0.0000	0.0000	0.0000
PP	0.0000	0.0000	0.0000	0.0000
	Finan. content		**Mod. Finan. content**	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
Method	Prob.	Prob.	Prob.	Prob.
Levin, Lin & Chu	0.0000	0.0000	0.0000	0.0156
Im, Pesaran and Shin	0.0000	0.0000	0.0000	0.0000
ADF	0.0000	0.0000	0.0000	0.0000
PP	0.0000	0.0000	0.0000	0.0000

our choice of PMG as preferred model. Stationarity of residuals of the PMG/ARDL model is tested due to panel unit root test. Results are reported in table A10. We concluded errors are stationary and, therefore, the relations estimated are not spurious.

Mathematical Appendix

For exposition purposes, lets divide the IO table between manufacture and non-manufacture sectors. The respective technical coefficients sub-matrices, $\mathbf{A}_{ij}$, are defined and given by:

$$\begin{aligned} \mathbf{A}_{RR} &= \mathbf{Z}_{RR}\hat{\mathbf{x}}_R^{-1} && (1)\\ \mathbf{A}_{RM} &= \mathbf{Z}_{RM}\mathbf{x}_M^{-1} && (2)\\ \mathbf{A}_{MR} &= \mathbf{Z}_{MR}\hat{\mathbf{x}}_R^{-1} && (3)\\ \mathbf{A}_{MM} &= \mathbf{Z}_{MM}\mathbf{x}_M^{-1} && (4) \end{aligned}$$

where $\mathbf{Z}_{RR}$ is a $(n-1)\times(n-1)$ matrix that captures the direct magnitudes of the inter-industry flows outside the manufacture sector; $\mathbf{Z}_{RM}$ corresponds to a $(n-1)\times 1$ vector of non-manufacture inputs used by manufacture; $\mathbf{Z}_{MR}$ is a $1\times(n-1)$ vector that stands for inter-industry flows going from manufacture industries to the remaining sectors of the economy; $\mathbf{Z}_{MM}$ gives manufacture inputs used by the manufacture sector itself; $\mathbf{x}_R$ is a $1\times(n-1)$ vector of non-manufacture total output such that $\hat{\mathbf{x}}_R$ stands as the respective $(n-1)\times(n-1)$ diagonal matrix; and finally, $\hat{\mathbf{x}}_M$ corresponds to manufacture's total output.

Furthermore:

$$\begin{aligned} \mathbf{x}_R &= \mathbf{i}^T\mathbf{Z}_{RR} + \mathbf{Z}_{MR} + \mathbf{V}_R && (5)\\ \mathbf{x}_M &= \mathbf{Z}_{RM}^T\mathbf{i} + \mathbf{Z}_{MM} + \mathbf{V}_M && (6) \end{aligned}$$

Table A9: MG/ARDL estimates

Long-run equation		
	Model 1	Model 2
Variable	Coefficient	Coefficient
Finan. content	-3.455824	1.686722

Short-run equation		
	Model 1	Model 2
Variable	Coefficient	Coefficient
Coint. Equation	-0.1015606***	-.0932464***
D(Finan. content)	-0.2129981	-0.1707817
C	0.0160907***	0.0147733***
Hausman statistic	1.1	1.11

*, **, and *** stand by 10%, 5% and 1% of significance. SBIC automatic lag-length selection.

Table A10: Panel Unit Root tests, residuals PMG/ARDL

PMG/ARDL	Intercept	Trend and Intercept
Method	Prob.	Prob.
Levin, Lin & Chu	0.0000	0.0000
Im, Pesaran and Shin	0.0000	0.0000
ADF	0.0000	0.0000
PP	0.0000	0.0000

such that $\mathbf{V}_R$ is a $1 \times (n-1)$ vector that captures value-added of non-manufacture activities and $\mathbf{V}_M$ corresponds to manufacturing value added. Finally, $\mathbf{i}$ corresponds to a $(n-1) \times 1$ vector of 1's.

If financial's value-added has been overestimated in the System of National Accounts (SNA), as argued by different authors, this means the true $\mathbf{V}_R$ is actually lower.[6] From Eq. (5) this implies that the true $\mathbf{x}_R$ is also smaller. Moreover, if distortions are increasing over time, there is a negative trend bias in manufacture content. In fact, substituting Eqs. (5) in (3) and computing the partial derivative on $\mathbf{V}_R$, we have:

$$\frac{\partial \mathbf{A}_{MR}}{\partial \mathbf{V}_R} = -\mathbf{Z}_{MR}[(\mathbf{i}^T\mathbf{Z}_{RR} + \mathbf{Z}_{MR} + \mathbf{V}_R)^{-1}]^2 < 0 \tag{7}$$

In other words, a negative trend in manufacture content could be simple driven by distortions in how financial value-added is measured. Motivated by the discussion provided by DF&P, we also perform our analysis making all FIRE incomes as intermediate inputs to the rest of the economy. Such manipulation of $\mathbf{V_R}$ allows us to provide a more robust analysis, especially in terms of data trends.

The two crucial variables to change are $\mathbf{Z}_{RR}$ and $\mathbf{Z}_{RM}$, i.e. the non-manufacture content of all productive sectors. One can partition those matrices so that:

$$\mathbf{Z}_{RR} = \begin{bmatrix} \mathbf{Z}_{\bar{R}\bar{R}} & \mathbf{Z}_{\bar{R}F} \\ \mathbf{Z}_{F\bar{R}} & \mathbf{Z}_{FF} \end{bmatrix} \tag{8}$$

and

$$\mathbf{Z}_{RM} = \begin{bmatrix} \mathbf{Z}_{\bar{R}M} \\ \mathbf{Z}_{FM} \end{bmatrix} \tag{9}$$

where $\mathbf{Z}_{\bar{R}\bar{R}}$ is a $(n-2) \times (n-2)$ matrix of inter-industry flows outside the manufacture and financial sectors; $\mathbf{Z}_{\bar{R}F}$ is a $(n-2) \times 1$ vector of non-manufacture non-financial inputs used by the financial sector; $\mathbf{Z}_{F\bar{R}}$ corresponds to a $1 \times (n-2)$ vector of financial inputs used by non-manufacture non-financial industries; $\mathbf{Z}_{FF}$ gives financial inputs used by the financial sector itself; $\mathbf{Z}_{\bar{R}M}$ is a $(n-2) \times 1$ vector of non-manufacture non-financial inputs used by manufacture industries; and finally, $\mathbf{Z}_{FM}$ stands for financial inter-industry flows going to the manufacture sector.

Furthermore, non-manufacture value-added can be decomposed as:

$$\mathbf{V}_R = \begin{bmatrix} \mathbf{V}_{\bar{R}} & \mathbf{V}_F \end{bmatrix} \tag{10}$$

such that $\mathbf{V}_{\bar{R}}$ is a $1 \times (n-2)$ vector of non-manufacture non-financial value-added and $\mathbf{V}_F$ stands for financial value-added. Hence, from Eqs. (8)-(10), the four variables to change are actually $\mathbf{Z}_{F\bar{R}}$, $\mathbf{Z}_{FF}$, $\mathbf{Z}_{FM}$, and $\mathbf{V}_F$, that are now redefined as:

$$\begin{aligned} \tilde{\mathbf{Z}}_{F\bar{R}} &= \mathbf{Z}_{F\bar{R}} + \mathbf{Z}_{F\bar{R}}\hat{\mathbf{s}} \\ \tilde{\mathbf{Z}}_{FF} &= \mathbf{Z}_{FF} + \mathbf{Z}_{FF}s_{ii} \\ \tilde{\mathbf{Z}}_{FM} &= \mathbf{Z}_{FM} + \mathbf{Z}_{FM}s_{ii} \\ \tilde{\mathbf{V}}_F &= 0 \end{aligned}$$

where, this time, $\hat{\mathbf{s}} = \{s_{ij}\}$ is a $(n-2) \times (n-2)$ diagonal matrix with $s_{ii} = \mathbf{V}_F / \sum_{j=1}^{n} z_{Fj}$, i.e. the ratio between FIRE's value-added and the sum of all financial inputs before redistribution.

[6]For a comprehensive discussion on these issues, see DF&P and the book by Assa (2016).

References

[1] Aghion, P.; Bloom, N.; Blundell, R.; Griffith, R. and Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics*, 701-728.

[2] Aghion, P.; Bechtold, S.; Cassar, L. and Herz, H. (2014). The causal effects of competition on innovation: Experimental evidence. *NBER Working Paper Series*, 19987.

[3] Assa J. (2016). *The Financialization of GDP*. New York, Routledge.

[4] Autor, D.; Dorn, D.; Katz, L.; Patterson, C. and Van Reener, J. (2017). Concentrating on the fall of the labor share. *NBER Working Paper*, 23108.

[5] Basu, D. and Foley, D. (2013). Dynamics of output and employment in the US economy. *Cambridge Journal of Economics* 37, 1077-1106.

[6] Blackburne III, E. and Frank, M. (2007). Estimation of nonstationary heterogeneous panels. *Stata Journal* 7(2), 197-208.

[7] Bezemer, D. (2016). Towards an Accounting View on Money, Banking and the Macroeconomy: History, Empirics, Theory. *Cambridge Journal of Economics* 40, 12751295.

[8] Bloom, N.; Draca, M. and Van Reenen, J. (2016). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *Review of Economic Studies* 83, 87117.

[9] Brennan, J. (2016). United States income inequality: The concept of countervailing power revisited. *Journal of Post Keynesian Economics* 39(1), 7292.

[10] Brooks, C. (2014). *Introductory Econometrics for Finance*. 3th edition, Cambridge University Press.

[11] Buera, F. and Kaboski, J. (2012). The Rise of the Service Economy. *American Economic Review* 102(6), 2540-2569.

[12] Buera, F.; Kaboski, J. and Rogerson, R. (2015). Skill Biased Structural Change. *NBER Working Paper Series*, 21165.

[13] Castellacci, F. (2010). Structural Change and the Growth of Industrial Sectors: Empirical test of a GPT model. *Review of Income and Wealth* 56(3), 449-482.

[14] Chenery, H. (1960). Patterns of Industrial Growth. *American Economic Review* 50, 624-653.

[15] Ciriaci, D. and Palma, D. (2016). Structural chang and blurred sectoral boundaries: assessing the extent to which knowledge-intensive business services satisfy manufacturing final demand in Western countries. *Economic Systems Research* 28(1), 55-77.

[16] Dávila-Fernández, M., Punzo, L. (2019). Financialisation as structural change: measuring the financial content of 'things'. *Economic Systems Research*. https://doi.org/10.1080/09535314.2019.1643294.

[17] Dolado, J. and Lütkepohl, H. (1996). Making Wald test work for cointegrated VAR systems. *Econometrics Reviews* 15(4), 369-386.

[18] Driver, C. (1994). Structural Change in the UK 1974-84: An Input-Output analysis. *Applied Economics* 26(2), 153-158.

[19] Dumitrescu, E. and Hurlin, C. (2012). Testing for Granger Non-causality in Heterogeneous Panels. *Economic Modelling* 29(4), 1450-1460.

[20] Epstein, G. (2005). Introduction: Financialization and the world economy. In Epstein, G. (ed.), *Financialization of the world economy*, pp. 3-16. Cheltenham: Edward Elgar.

[21] Feldman, S.; McClain, D. and Palmer, K. (1987). Sources of Structural Change in the United States, 1963-78: An Input-Output Perspective. *Review of Economics and Statistics* 69(3), 503-510.

[22] Franke, R. and Kalmbach, P. (2005). Structural change in the manufacturing sector and its impact on business-related services: an input-output study for Germany. *Structural Change and Economic Dynamics* 16, 467488.

[23] Galston, W. and Hendrickson, C. (2018). A policy at peace with itself: Antitrust remedies for our concentrated, uncompetitive economy. *Brookings Report*. https://www.brookings.edu/research/a-policy-at-peace-with-itself-antitrust-remedies-for-our-concentrated-uncompetitive-economy. Access in 10.05.2018.

[24] Gereffi; Humphrey and Sturgeon (2005). The governance of global value chains. *Review of International Political Economy* 12(1), 78-104.

[25] Im, K. S., M. H. Pesaran, and Y. Shin. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics* 115, 53-74.

[26] Incera, A. (2017). Drivers of change in the European youth employment: a comparative structural decomposition analysis. *Economic Systems Research* 29(4), 463-485.

[27] Johansen, Soren (1995). *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press.

[28] Krippner, G. (2005). The financialization of the American Economy. *Socio-Economic Review* 3, 173-208.

[29] Lanzafame, M. (2014). The balance of payments-constrained growth rate and the natural rate of growth: new empirical evidence. *Cambridge Journal of Economics* 38(4), 817-838.

[30] Leontief, W. (1941). *The Structure of American Economy 1919–1939*. New York: Oxford University Press.

[31] Leung, D. and Secrieru, O. (2012). Real-financial linkages in the Canadian economy: An Input-Output approach. *Economic Systems Research* 24(2), 195-223.

[32] Liu, R. and Rosell, C. (2013). Import competition, multi-product firms, and basic innovation. *Journal of International Economics* 91, 220-234.

[33] Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Springer-Verlag.

[34] McCarthya, I. and Anagnostoub, A. (2004). The impact of outsourcing on the transaction costs and boundaries of manufacturing *International Journal of Production Economics* 88(1), 61-71.

[35] Milberg, W. (2008). Shifting sources and uses of profits: sustaining US financialization with global value chains. *Economy and Society* 37(3), 420-451.

[36] Milberg, W. and Winkler, D. (2010). Financialisation and the dynamics of offshoring in the USA. *Cambridge Journal of Economics* 34(2), 275-293.

[37] Mion, G. and Zhu, L. (2013). Import competition from and offshoring to China: A curse or blessing for firms?. *Journal of International Economics* 89, 202-215.

[38] Montresor, S. and Marzetti, G. (2010). Outsourcing and structural change. Application to a set of OECD countries. *International Review of Applied Economics* 24(6), 731-752.

[39] Montresor, S. and Marzetti, G. (2011). The deindustrialisation reconsidered: a subsystem application to the OECD7. *Cambridge Journal of Economics* 35, 401-421.

[40] OECD (2017). How to make trade work for all. In *OECD Economic Outlook* 1.

[41] Palley, T. (2013). *Financialization: the economics of finance capital domination*. Palgrave McMillan.

[42] Palma, G. (2008). De-industrialisation, 'premature' de-industrialisation and the Dutch Disease. In Durlauf, S. and Blume, L. (ed.), *The New Palgrave Dictionary of Economics*. Second Edition. Palgrave Macmillan.

[43] Peneder M.; Kaniovski, S. and Dachs, B. (2003). What follows tertiarisation? Structural change and the role of knowledge-based services. *Service Industries Journal* 23(2), 47-66.

[44] Peneder M. and Streicher, G. (2017). De-industrialisation and comparative advantage in the global value chain. *Economic Systems Research*. Advanced online publication http://dx.doi.org/10.1080/09535314.2017.1320274.

[45] Pesaran, M. H., and R. P. Smith. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics* 68, 79-113.

[46] Pesaran, M.; Shin, Y. and Smith, R. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association* 94, 621-34.

[47] Risso, W.; Punzo, L. and Carrera, E. (2013). Economic growth and income distribution in Mexico: A cointegration exercise. *Economic Modelling* 35, 708-714.

[48] Rodrik, D. (2016). Premature deindustrialisation. *Journal of Economic Growth* 21, 1-33.

[49] Rose, A. and Chen, C. (1991). Sources of change in energy use in the US economy, 1972-1982: a structural decomposition analysis. *Resources and Energy* 13, 1-21.

[50] Rose, A. and Casler, S. (1996). Input-Output Structural Decomposition Analysis: A Critical Appraisal. *Economic Systems Research* 8(1), 33-62.

[51] Rowthorn, R. and Coutts, K. (2004). De-industrialisation and the balance of payments in advanced economies. *Cambridge Journal of Economics* 28(5), 767-790.

[52] Savona, M. and Lorentz, A. (2006). Demand and Technology Determinants of Structural Change and Tertiarisation: An Input-Output Structural Decomposition Analysis for four OECD Countries. LEM Papers Series 2005/25, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

[53] Seabrooke, L. and Wigan, D. (2017). The governance of global wealth chains. *Review of International Political Economy* 24(1),1-29.

[54] Toda, H. and Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics* 66, 225-250.

[55] Toh, M. and Thangavelu, S. (2013). An Input-Output study of the Singapore information sector *Economic Systems Research* 25(2), 233-244.

[56] Tregenna, F. (2009). Characterizing deindustrialisation: An analysis of changes in manufacturing employment and Output internationally. *Cambridge Journal of Economics* 33, 433-466.

[57] van der Zwan, N. (2014). Making sense of financialization. *Socio-Economic Review* 12, 99-129.

[58] Wiersema, M. and Bowen, H. (2008). Corporate diversification: The impact of foreign competition, industry globalization, and product diversification. *Strategic Management Journal* 29, 115132.