Stealth Consolidation, Market Power and Income Inequality *

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Abstract

Market power allows firms to capture a larger share of society surplus and to concentrate it in the hands of few. However, there is scant evidence on the relationship between market power and income inequality. This paper uses stealth consolidation in a dynamic factor model to identify exogenous variations in market power and their effect on the economy, a novel methodology that allows to overcome limitations in the data. Results show that the identified market power shock lowers output, but it increases the share of output that goes into profits. Moreover, it increases income and labor earnings inequality on impact, and this is mainly due to an earnings loss for the poor. The identified shock accounted for an increase in income Gini index by 0.4 between 2001 and 2006, and it can account for 20% of the variation in inequality. Therefore, this paper provides evidence of a causal link between market power and income inequality. (JEL: C32, D31, L16, L40)

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1 Introduction

Antitrust authorities foster competition so as to ensure that society surplus is shared among all agents in the economy. In the absence of competition, firms can exercise their market power so as to gain a larger share of this surplus. This redirects resources in the hands of few, at the expenses of many, and thus it generates an increase in inequality. There is, however, a lack of empirical evidence on the relationship between market power and income inequality, and this paper aims at filling this gap. In order to do so, this work devises a methodology that can be applied on publicly available data to identify exogenous variations in market power. This identification strategy exploits stealth consolidation in a dynamic factor model. Stealth consolidation, a concept introduced by Wollmann (2019), is defined as a plethora of anticompetitive deals that go unnoticed by antitrust authorities. These authorities tend to focus their attention and resources on large mergers. The rationale behind such policy is that small mergers are thought to have minor effects on market structure. Despite their unassuming size, however, these deals affect local or segmented markets where they can lead to duopolies or even monopolies. Stealth consolidation, then, provides a mean to identify exogenous variations in market power and their effect on the whole economy.

This work analyzes a determinant of income inequality that has not received much consideration in the empirical literature, despite the attention that inequality gathered recently (see Piketty (2014)). This paper shows that an increase in market power causes an increase in income inequality. Market power is defined as the ability of a firm to influence the market (e.g. by raising markups or lowering quantities) so as to gain more profits. It is therefore a chief candidate for increasing inequality. By increasing profits, firms are taking a larger portion of the wealth produced by society and they are redistributing it only to their shareholders. Since the richer part of the population owns a disproportionate share of firms capital, an increase in market power benefits the rich at the expenses of the poor. At the same time, monopsony power in the labor markets allows firms to lower wages and earnings, and this is particularly true for small and local labor markets, where earnings and productivity are already low[1]. These two mechanisms generate an increase in income inequality. The effect of stealth consolidation on market power, then, could explain part of the trend of increasing markups (De Loecker, Eeckhout, and Unger (2020)), raising profit share and falling labor share (Barkai (2019)), as well as the trend of increasing inequality (Heathcote, Perri, and Violante (2010)). This paper, therefore, fits into the debate on whether merger policy should be more or less restrictive, by showing that stealth consolidation can have far reaching consequences on the whole economy.

The lack of empirical work on the relationship between market power and income inequality is in part

[1]Berger et al. (2019) show that monopsony power is higher in small and concentrated labor markets. Manning (2011) claims that in low skilled labor markets it is more common wage-posting, a model of imperfect competition in which concentration decreases wages.

due to the lack of a unified dataset covering the whole economy. This paper contributes to the existing literature by providing a novel identification strategy to overcome such limitation and by showing evidence on the effect of market power on income inequality. Given a product market, an exogenous increase in market power affects the income of workers and owners of competing firms through different channels. It is not possible, however, to identify these workers and owners for any product market and any industry in the US. Consequently, one cannot construct a reliable control group from the population. As a way to deal with such data limitation, this paper proposes a novel method to identify exogenous variation in market power by using stealth consolidation. Then it leverages a large dimension dataset in a dynamic factor model so as to infer the effect of these exogenous changes on the whole economy, and ultimately on income inequality.

How can one identify a macroeconomic shock that captures stealth consolidation? This paper exploits variations between the number of horizontal and non horizontal mergers that are exempt from reporting under the Hart-Scott-Rodino Act. These are mergers whose transaction value is below a defined threshold and as such they will be called stealth mergers, as authorities have no way of detecting them. Horizontal mergers are defined as transactions between companies operating in the same industry, and thus they are most likely to decrease incentives to compete and to increase market power[2]. This interpretation is in line with the US Antitrus Authorities: since 1992 merger evaluation procedures are titled "Horizontal Merger Guidelines". A market power shock is identified as the residual portion of the number of stealth horizontal mergers which is not explained by non horizontal ones[3]. As a consequence a positive shock can be interpreted as an unexpected increase in the number of stealth horizontal mergers with respect to non horizontal ones[4]. Since horizontal mergers are the ones that have the potential to increase market power, this can be considered a macroeconomic shock to market power. This is accomplished in a recursive identification scheme applied on stealth M&A activity and factors estimated in a Dynamic Factor Model[5], a methodology commonly referred to as Factor Augmented Vector Auto Regression (FAVAR).

In order to understand the effects of an increase in market power on the whole economy one needs to take into account all relationships between macroeconomic quantities, and this is possible through a Dynamic Factor Model[6] (DFM). These models, which can be considered an extension of the Vector Autoregressive (VAR) methodology to large datasets[7], condense common co-movement of variables by estimating unob-

[2]As Wollmann (2019) reports, horizontal mergers are more likely to reduce rivalry.

[3]In particular, the market power shock is identified as the shock that moves only the number of stealth horizontal mergers on impact, but it does not move the number of stealth non horizontal mergers contemporaneously.

[4]Non horizontal mergers act as a control, by taking into account any factor that might influence merger activity (e.g. credit market conditions, expectations on future economic performance)

[5]Similarly to the work of De Giorgi and Gambetti (2017) on productivity and uncertainty shocks

[6]see Forni et al. (2009)

[7]By using DFM one can replicate existing results that were obtained using VAR methodologies and extend them to larger datasets. As an example, this work shows how to identify a technology shock a là Galí and Rabanal (2004) and shows that it

servable factors[8]. Then standard time series methodologies are applied to these factors. Although short run fluctuations in inequality are relevant to understand part of the social cost of the business cycle, one is typically interested in long run changes in income distribution. Following the work of Barigozzi, Lippi, and Luciani (2016), long run features of the data are explicitly modeled in a Vector Error Correction (VEC) framework, which accounts for cointegration. This allows to draw conclusions on the short and on the long run consequences of an increase in market power.

In practical terms, this is an empirical work that exploits time sieries methods applied to large dimensional datasets, so as to provide evidence that an increase in market power generates an increase in inequality. Data on firms come from Compustat, a database of publicly traded firms in the US, with the aim of covering the largest cross section of firms available[9]. On top of that, data on mergers come from Thompson and Reuters SDC Platinum, which features transaction level data, as in Wollmann (2019). On the household side, census level data[10] allow to reconstruct the distribution of income, earnings, working hours and consumption, and to study their evolution over time[11]. This gives much more insight than simply looking at inequality measures such as Gini indexes.

The identified shock raises M&A activity and lowers GDP on impact, as one would expect after an increase in market power. Moreover it decreases TFP for several years, showing that mergers efficiencies are not generated immediately. The shock increases firms' markups, a key measure of market power, and high markup firms show a stronger rise[12]. Income and labor earnings decreases for poor households, but they increase for rich ones, which are able to share rents with firms. This directly generates an increase in inequality, which is reflected by the Gini index response.

Even more interesting is the effect of a shock to M&A activity in the long run. Output eventually increases, together with TFP, showing that M&A create efficiencies that need time to fully realize. This shows that antitrust policies should take into account both short and long run effects of perspective mergers, rather than focusing only on immediate outcomes. The shock increases also the share of output that goes into profits in the long run. Households income increases in the long run, driven by the increase in output, but rich households gain much more than poor ones. A similar pattern can be seen in earnings. This generates a permanent and significant increase in inequality, several years after the shock hit the economy.

increases inequality in the short run.

[8]These are linear combinations of variables built by using principal components.

[9]Recent development in the literature allow to compute measures of market power at the firm level, and reveal that aggregation obscures a large portion of the variability in such measures, as shown by De Loecker, Eeckhout, and Unger (2020).

[10]Data for households are taken from the Consumption and Expenditure Survey (CEX), a periodical survey conducted by the Bureau of Labor Statistics in US.

[11]see Heathcote, Perri, and Violante (2010) for a thorought description of the dataset

[12]In accordance with De Loecker, Eeckhout, and Unger (2020), who observe that high markup firms are the ones responding the most to macroeconomic shocks

As a consequence, antitrust policy should take into account also the distributional implications of increases in market power.

The model of this work can be used also to quantify effects of a sudden increase in horizontal mergers. Wollmann (2019) shows that the Amendment to the Hart-Scott-Rodino Act in December 2000 caused an increase of about 320 horizontal M&A deals per year. This work shows that a shock of similar magnitude increases the income Gini index by 1 Gini points in the long run[13]. In accordance with this result, it is shown through Error Variance Decomposition that the identified shock to market power accounts for 20% of the forecast error variance of Gini indexes in the long run. Moreover, through an historical decomposition of Gini index, this work shows that the identified market power shock accounted for an increase of about 0.4 Gini points between 2001 and 2006.

Changes brought at the macroeconomic level by the identified shock are shown to be relevant also at the indsutry level. In 20 industries out of the 23 analyzed the shock increased the number of mergers, and in 15 industries the level of markups followed the response of M&A activity. Overall, the identified shock to market power concentrated almost all analyzed industries and it generated a widespread increase in markups. This shows that the shock propagated throughout the majority of the analyzed industries, and as such it affected the entire supply side of the economy.

Lastly, this work provides several robustness checks of the main results. Alternative orderings and control variables are explored for the recursive identification strategy. The main results of this paper are shown to be robust to alternative ways of measuring merger activity[14] and alternative ways of measuring markups[15]. Moreover, this work explores a more agnostic identification procedure, based on Antolín-Díaz and Rubio-Ramírez (2018) narrative sign restrictions. This alternative identification scheme produces results that are very similar to the ones that obtain in the recursive framework. Overall, this sensitivity analysis provides evidence for a unique conclusion: the identified shock to market power increases income inequality, both in the short and in the long run.

Related Literature

This paper is clearly related to the work of Wollmann (2019) and it is meant to be an extension of its results to the whole macroeconomy, and eventually to income inequality. Wollmann (2019) studies an Amendment to the Hart-Scott-Rodino Act that raised the threshold under which merging parties were exempt from reporting

[13] 1 Gini point is roughly equivalent to 2.5% of income Gini in 2001

[14] Measuring M&A activity with the number of deals, or with the value of such deals.

[15] Results hold when markups are computed with or without fixed costs in the production function. Results are robust even for markups computed using the Lerner Index.

their transactions to US authorities. By using a Diff-in-Diff identification strategy, Wollmann shows that the Amendment increased the number of horizontal mergers, raising concentration in the economy. The autor uses the term stealth consolidation to describe a widespread surge in small mergers that go under the radar of US authorities. Albeit small on paper, these transactions affect many local product markets, and they can increase significantly the level of market power in many sectors.

Furthermore, this work fits into the emerging literature that tries to apply rigorous time series methods to the evolution of inequality. The closest paper in this literature is De Giorgi and Gambetti (2017), in which the authors use the same data and a DFM to study the effect of a shock to productivity and uncertainty on consumption inequality at business cycle frequencies. The authors show that the identified shocks reduce consumption inequality on impact. Mumtaz and Theophilopoulou (2017) apply a VAR methodology, combined with sign restrictions, in order to study the effect of a monetary policy on income and consumption inequality in the short run. They use UK data an find that a contractionary monetary policy shock increases inequality. Olivier Coibion et al. (2017) answer a similar question for the US using a narratively identified monetary shock and local projections a là Jordà (2005). Anderson, Inoue, and Rossi (2016) study fiscal shocks in a VAR framework using narrative identification, and find that government spending shocks decrease consumption inequality in the US.

This paper contributes to this strain of literature on two dimensions. First, rather than studying the effect of standard macroeconomic shocks already identified in the literature, it provides a new strategy to identify a shock to market power. To the best of my knowledge, no other work uses data on M&A activity to identify a market power shocks in a time series framework. Second, rather than focusing on business cycle frequencies, my work models explicitly the cointegration structure of the data and provides significant evidence on long run effects on inequality. To the extent of my knowledge, no other paper applies cointegration methods to income inequality.

Other works try to relate firms activity to income inequality. Some are descriptive, such as the work of Song et al. (2019) who use a massive matched employer-employee database to ascertain firm contribution to the rise in earnings inequality. Others face the question from a theoretical point of view. Boar and Midrigan (2019) build a model with heterogeneous agents that act as entrepreneurs for heterogeneous firms, and show that size dependent subsidies can reduce markup dispersion and increase welfare[16]. Colciago and Mechelli (2019) build an heterogeneous agents model with oligopolistic competition, by embedding Cournot and Bertrand competition in an Aiyagary model. They find that lowering competition increases profits and inequality. Eggertsson, Robbins, and Wold (2018) modify a standard neoclassical model to show how an increase in market power can explain declining interest rates and labor share[17]. There are also papers in the

[16]Their model, however, relies on large publicly traded firms that redistribute profits to the whole population.

[17]Although Eggertsson, Robbins, and Wold (2018) work in a representative agent framework, the authors argue that market

Law and Economics literature on antitrust arguing that market power has an effect on inequality[18].

Notwithstanding the early work of Parker (2000) on why panel methods should not be applied to inequality, the previous empirical literature focused on panel data methods[19] and tried to find determinants of inequality in standard macroeconomic variables or in macroeconomic volatility. The empirical literature describing trends and features of inequality is flourishing, both for the US (Heathcote, Perri, and Violante (2010); Guvenen, Ozkan, and Song (2014); Song et al. (2019)) and for other countries (Blundell and Etheridge (2010); Jappelli and Pistaferri (2010); Krueger et al. (2010)). The teoretical litearature on inequality is flourishing as well, thanks to the development of Heterogeneous Agents New Keynesian models (Bhandari et al. (2018); Kaplan et al. (2018)). On the other hand, the literature on markups and market power expands both theoretically (Edmond, Midrigan, and Xu (2018); Gutiérrez, Jones, and Philippon (2019)) and empirically (Nekarda and Ramey (2013); Blonigen and Pierce (2016); Galı, Gertler, and Lopez-Salido (2017); De Loecker, Eeckhout, and Unger (2020); Dıez, Fan, and Villegas-Sanchez (2019)). This work fits also into the literature of structural Dynamic Factor Models (Giannone, Reichlin, and Sala (2005), Forni et al. (2009)) and it applies the recently developed methodologies of Barigozzi, Lippi, and Luciani (2016) to estimate DFM on non stationary data.

The rest of the paper is structured as follows. Section 2 describes the dataset, comprising households, firms and macroeconomic variables. Section 3 covers the empirical strategy, and in particular it describes Factor Error Correction Models and it discusses identification. Section 4 reports the main results, as well as robustness checks. Section 5 concludes.

2 Data

Given the nature of this work, the dataset on which the analysis is conducted is large and diversified. Overall the time series dimension spans from 1980Q1 up to 2006Q4, and the data are on quarterly frequency[20].

power can have sizable effects on inequality.

[18]See for instance Elhauge (2015) or Khan and Vaheesan (2017)

[19]See as an example Iyigun and Owen (2004), Breen and Garcia-Penalosa (2005) and Jäntti and Jenkins (2010)

[20]Current time series limitations are due mainly to availability of data on household variables. The main results hold qualitatively for an analysis run on an alternative dataset constructed from raw CEX data from 1980Q1 to 2012Q4.

2.1 Households

Data on households Income, Earnings, Consumption and Labor Hours are gathered from the Consumption and Expenditure Survey (CEX)[21]. It is a rotating panel of households that are selected to be representative of the US population[22]. Each household is interviewed for a maximum of four consecutive quarters. This survey reports, for the cross section of households interviewed, detailed demographic characteristics for all household members, detailed information on consumption expenditures for the three-month period preceding the interview, and information on income, labor earnings, hours worked, and taxes paid over a yearly period.

Overall the sample varies from about 2500 to about 4000 households interviewed in each quarter, and it is built to be representative of the whole US population. This allows for the computation of standard measures of inequality, such as the Gini coefficient, for each variable considered. Moreover, households are divided in income deciles, so that each decile contains a minimum of 240 households in 1980 and a minimum of 400 households in 2006. Then for each income decile one can compute the average Income, Earnings, Labor Hours and Consumption. On top of that. households can be divided by education level of the head[23]. Households are divided into those that have an education level lower or equal to High School, and those who have an education level greater or equal than College. Then for each group one can compute average Income, Earnings, Labor Hours and Consumption. These decile averages, together with averages by education and Gini indexes, will be the main dependent variables of the analysis.

2.2 Firms

If income inequality is the main dependent variable of this study, then firms' market power is the main explanatory variable. There are several ways to measure market power, and this work explores a variety of them.

2.2.1 Disaggregated Markups

A first measure of market power comes from markups, defined as the ratio between sales price and marginal cost. Prices and sales are relatively easy to measure, but the challenge faced by researchers stands in the computation of marginal costs. This work follows the methodology of De Loecker, Eeckhout, and Unger

[21]The dataset is thoroughly described in Heathcote et al. (2010) and it was used by previous work on Income and Consumption distributions such as Coibion et al. (2017), De Giorgi and Gambetti (2017) and Anderson et al. (2016).

[22]Continuous and reliable data are available only from the first quarter of 1980, which is the start of the analyzed sample.

[23]the oldest male, or the oldest female if no male is present

(2020)[24] applied to Compustat data, which covers publicly traded firms starting in 1950[25]. The choice of the dataset is directed mainly at covering the widest possible array of firms and industries over the longest time horizon. Although publicly traded firms are not the majority of operating firms in US, they account for 41% of private sales and 29% of private US employment.

Appendix A reports details on both data and methodology used to compute markups. The researcher has to make explicit assumptions on the production function of firms, and this work assumes a translog poduction function. The production function is estimated under a further assumption of constant sector level elasticity of output to variable inputs θ_s^v. Markups are computed as the product between such elasticity and the ratio of output to variable input[26]:

$$\mu_{it} = \theta_s^v \frac{\text{Output}_{it}}{\text{Variable Input}_{it}}$$

Markups are computed at the firm level, but for the empirical analysis they are aggregated in two ways. First, they are divided in deciles, similarly to what is done for household data, and then for each decile it is computed the harmonic average weighted by sales. Secondly, they are aggregated at the sector level, using 2-digit NAICS sectors so as to be consistent with the sector level elasticities.

2.2.2 Aggregated Measures

The recent literature produced also refined measures of aggregate market power and markups for the US economy. One of the first candidates is the Profit Share, which can be obtained from FRED and is defined as profit per unit of real gross value added of non-financial corporate business.

Another determinant of the level of market power in US is M&A Activity[27], which is captured by the dataset on Mergers and Acquisitions provided by Thompson Reuters SDC Platinum[28]. Wollmann (2019) uses the same database to asses the effect of an Amendment to the Hart-Scott-Rodino Act, which raised the threshold under which parties are exempt from reporting their transaction to the authorities. This work focuses on transactions that are exempt under the Hart-Scott-Rodino Act[29]. These transactions are labeled as stealth mergers, since merging parties are not required to report them to the authorities. Two main

[24] which was previously developed by De Loecker and Warzynski (2012)

[25] although reliable quarterly data are available only from the 80s'

[26] for more details, refer to the Appendix

[27] Gutiérrez, Jones, and Philippon (2019) identify an Entry Cost shock that raises profits and concentration, and show that it correlates with M&A activity as measured from SDC. The shock Gutiérrez, Jones, and Philippon (2019) identify is conceptually very close to the one analyzed in this work, as the authors interpret it as decreasing competition.

[28] Blonigen and Pierce (2016) use the same dataset to show that M&As are associated with increases in average markups, but find little evidence for effects on productivity.

[29] meaning those transactions whose value is below 50 million dollars (in 2000 USD)

measures are constructed from this dataset: the number of stealth horizontal M&A deals, and the number of stealth non-horizontal M&A deals. Horizontal deals are defined as deals between firms in the same four-digit SIC industry, and are meant to capture deals regarding the same product markets. As such, horizontal deals represent anticompetitive increases in concentration, and they will be confronted with non horizontal deals in the identification of market power shock.

2.3 US Economy

As a control for the rest of the economy, several other macroeconomic variables are introduced into the dataset. In particular this work uses 101 macroeconomic series in levels provided by Barigozzi, Lippi, and Luciani (2016)[30]. Moreover, the dataset includes measures of Total Factor Productivity (TFP) provided by Fernald (2014) at quarterly frequency, and adjusted for utilization.

3 Empirical Strategy

In order to take full advantage of the extensive dataset available for this work a Large Dimensional Dynamic Factor Model (DFM) is the natural choice. These models became popular in the econometric and macroeconomic literature in the early 2000s and have been successfully used for policy analysis based on impulse response function[31]. DFMs represent the intuition that all variables in the economy are driven by few common macroeconomic shocks, with their residual component being idiosyncratic.

DFMs allow the researcher to infer causal relationships from a very large pool of time series data, exploiting the common movement of macroeconomic series. In doing so, they rely on a small set of assumptions that are clearly stated in the definition of the model. Although DFMs can be considered an extension of Vector Auto Regressive methods (VAR), they do not suffer from the issue of non-fundamentalness, which arises when agents form choices based on expectations of future variables, and makes VAR impossible to estimate[32]. Besides, DFM can be used to replicate VAR analysis[33].

Moreover, aternative methods such as panel regressions are affected by the issue of spurious correlation[34]

[30]This wide dataset well approximates the information set available to a large institution, for instance a central bank.

[31]see as reference Giannone, Reichlin, and Sala (2005), Stock and Watson (2005), Forni et al. (2009), Forni and Gambetti (2010), Barigozzi, Conti, and Luciani (2014) and De Giorgi and Gambetti (2017), whose methodology is the closest to this work

[32]see Forni, Gambetti, and Sala (2014)

[33]Appendix D shows that one can identify a technology shock a là Galí and Rabanal (2004) using a DFM applied to the dataset of this paper. In accordance with the work of De Giorgi and Gambetti (2017), a technology shock increases income inequality. On top of that, the technology shock increases firms' markup, and high markup firms show a stronger increase.

[34]see Parker (2000)

that arises whenever dependent and independent variables are not stationary, which is the case for most of the variables describing income inequality. On the other hand, recent results of Barigozzi, Lippi, and Luciani (2016) show that DFMs can be successfully applied to non-stationary data by imposing and error correction structure on the factors. This allows the researcher to make reliable inference at all frequencies, and especially in the long run.

3.1 Factor Error Correction Models

At the core of a DFM there is the assumption that the data x_{it} can be decomposed into the sum of two unobservable components, the common component χ_{it} and the idiosyncratic component ξ_{it}

$$x_{it} = \chi_{it} + \xi_{it}$$

Where $i \in \{1...N\}$ represents the cross section and $t \in \{1...T\}$ represents the time series dimension. A further assumption of any DFM is that the common component of each variable i is a linear combination of r common factors $F_t = (F_{1t}, ..., F_{rt})'$:

$$\chi_{it} = \lambda_{i1}F_{1t} + ... + \lambda_{ir}F_{rt} = \lambda_i F_t$$

Where the vector $\lambda_i = (\lambda_{i1}, ..., \lambda_{ir})$ is called factor loading of variable i. These represent the weight that is given to each factor in determining the common component of variable i.

Most of the literature on DFM considers stationary data, and thus it imposes a simple VAR structure on the factors $C(L)F_t = Ru_t$, where L represents the lag operator, and u_t are the structural shocks that drive the whole system. Given the non-stationary nature of x_{it}, which implies non-stationarity of the factors F_t, the results of Sims, Stock, and Watson (1990) show that the parameters of VAR in levels on the factors are consistently estimated. Nonetheless, Phillips (1998) shows that in the presence of cointegration long run IRF are consistently estimated only if one models the long run properties of the system, i.e. within a Vector Error Correction Model (VECM). Therefore this work imposes a VECM specification on the factor dynamics, so as to reliably estimate IRF also in the long run:

$$G(L)\Delta F_t = h + \alpha\beta' F_{t-1} + Ru_t \tag{1}$$

Where $G(L)$ is a matrix of lag polynomials, h is a vector of constants, α is a r x c matrix of weights and β is the r x c matrix describing c cointegrating relationships between factors. Lastly R is a r x r rotation matrix that rotates the shocks u_t so as to achieve identification.

By defining:

$$x_t = (x_{1t}, ..., x_{Nt})',\ \chi_t = (\chi_{1t}, ..., \chi_{Nt})',\ \xi_t = (\xi_{1t}, ..., \xi_{Nt})',\ \Lambda = (\lambda_1, ..., \lambda_N)'$$

One can write the Factor Error Correction Model (FECM) that is used in this work:

$$\begin{aligned} x_t &= \chi_t + \xi_t = \Lambda F_t + \xi_t \\ G(L)\Delta F_t &= h + \alpha\beta' F_{t-1} + Ru_t \end{aligned} \tag{2}$$

Barigozzi, Lippi, and Luciani (2016) show that factors F_t and factor loadings Λ of non stationary data can be consistently estimated by using principal components, the standard tool of DFM. Given the sample convariance $\hat{\Gamma} = T^{-1}\Delta x \Delta x'$, one can compute the n x r matrix $\hat{W}$ containing the r eigenvectors of $\hat{\Gamma}$ corresponding to the r largest eigenvalues of $\hat{\Gamma}$. Then the estimated factors and factor loadings are:

$$\hat{\Lambda} = \sqrt{N}\hat{W}, \quad \hat{F}_t = \frac{1}{\sqrt{N}}\hat{W}x_t = \frac{1}{N}\hat{\Lambda}' x_t$$

With regard to the estimation of the Impulse Response Function of a VECM one can refer to Lütkepohl (2006). Suffices to say that, given the number of lags p, one has to estimate the matrix polynomial[35]:

$$\hat{A}^{VECM}(L) = I_r - \sum_{k=1}^{p+1} \hat{A}_k^{VECM} L^k$$

So that the IRF of the VECM in the factors is:

$$IRF^{VECM} = \left[\hat{A}^{VECM}(L)\right]^{-1} R$$

The matrix R is an orthogonal rotation matrix with the properties $RR' = I$ and $det(R) = 1$ that serves as identification matrix. As such it is chosen by the researcher to identify a desired shock.

Once IRF for the factors F_t has been estimated, one can easily construct IRF for the variables $x_t = \Lambda F_t + \xi_t$ thanks to the factor loadings Λ:

$$IRF^{FECM} = \hat{\Lambda}\left[\hat{A}^{VECM}(L)\right]^{-1} R$$

Therefore the Impulse Response of valriable i to shock j, as identified by column r_j of matrix R, can be written as:

$$IRF_{ij}^{FECM} = \hat{\lambda}_i \left[\hat{A}^{VECM}(L)\right]^{-1} r_j$$

Proposition 1 of Barigozzi, Lippi, and Luciani (2016) proves that, as $N, T \to \infty$ such Impulse Response is consistent. The authors prove consistency also for an IRF computed using VAR in levels on the factors, but

[35]With coefficients given by:

$$\begin{aligned} \hat{A}_1^{VECM} &= \hat{G}_1 - \alpha\beta' + I_r \\ \hat{A}_k^{VECM} &= \hat{G}_k - \hat{G}_{k-1}, \quad k = 2, ..., p \\ \hat{A}_{p+1}^{VECM} &= -\hat{G}_p \end{aligned}$$

note that such consistency holds only for finite horizons, and as such long run IRF based on VAR in levels are no longer consistent.

One last step that is needed for the estimation of the model is to determine the number of static factors r and the number of unit roots τ for the VECM dynamics. With regard to r, Bai and Ng (2002) devise the standard test that is commonly used in the literature. The test applied to the extended dataset indicates a number of static factors $r = 7$. Barigozzi, Lippi, and Luciani (2016) extend the test of Hallin and Liška (2007) and devise a test for the number of shocks driving the data[36]. Similarly to the results of Barigozzi, Lippi, and Luciani (2016), this works finds $\tau = 1$[37].

For the results presented in this work, $r = 7$ static factors and factor loadings are estimated using principal components on data in levels. Relevant variables, including GDP and deciles for income, earnings, hours and consumption, are detrended using a linear trend[38]. Then, the estimation proceeds onto a VECM with $\tau = 1$ unit roots. Identification is conducted as described in the following section.

3.2 Identification

The problem of identification for DFMs amounts to finding an appropriate rotation matrix R for the shocks u_t, similarly to identification in standard VAR settings. This allows to identify the structural shocks $\epsilon_t = Ru_t$. Before such rotation, the shocks u_t have little interpretation, and the choice of R determines the shape of Impulse Response Functions. The aim of this work is to identify a shock to market power, and describe its effects on income inequality.

3.2.1 Stealth M&A

Mergers and Acquisitions (M&A) are commonly associated with an increase in market power. The merger between two firms operating in the same sector increases concentration and reduces incentive to compete, as well as increasing the ability of incumbents to prevent new entry. Blonigen and Pierce (2016) show that M&As increase markups without increasing productivity or efficiency, a clear sign of increasing market power. Gutiérrez and Philippon (2017) use discrete jumps in concentration following large M&A to identify changes in competition. In their recent work Gutiérrez, Jones, and Philippon (2019) use a calibrated DSGE model

[36]The test is based on the number of diverging eigenvalues of the spectral density of Δx, called $\Sigma(\theta)$. When one considers the eigenvalues of $\Sigma(0)$, the spectral density at long run frequency 0, then the test selects the number of common trends τ.

[37]For more details on the testing procedure, refer to Appendix B.

[38]As recommended in Barigozzi, Lippi, and Luciani (2016). Variables that are not detrended include Gini indexes as well as markups.

together with maximum likelihood methods to estimate a shock to entry costs. The authors claim that such a shock represents variations in competition, and show that it has had a significant effect on macroeconomic dynamics over the past 30 years. As further evidence, the authors show that their shock correlates well with M&A activity.

By treating M&A activity as a signal of increasing market power, one can use it as a known factor[39] and study how it influences the dynamics of the other factors driving the economy. This can be done by using a standard recursive identification scheme. This is a well known methodology in the literature on structural DFMs, as one can see in De Giorgi and Gambetti (2017), and usually it takes the name of Factor Augmented Vector Acutoregression (FAVAR).

M&A Activity correlates with many macroeconomic variables, and as such there is a clear endogeneity issue whenever one tries to use it to identify a shock to market power. In order to control for anything that might affect merger dynamics, such as credit market conditions, this work exploits the difference between horizontal and non-horizontal mergers. Horizontal M&A are defined as transactions between companies operating in the same narrowly defined industry, and as such they increase concentration and can raise market power in a determined product market[40]. The identified market power shock is defined as a change in the number of horizontal mergers with respect to the number of non horizontal ones.

On top of that, this work will focus on those mergers that usually go under the radar of the US authority, and as such they are referred to as Steath Consolidation by Wollmann (2019). These are transaction whose value is below the threshold defined by the Hart-Scott-Rodino Act. This threshold was revised in December 2000 up to 50 million USD by and Amendment to the same act. Mergers that are small enough to be under this threshold are not required to report to the US authorities, and as such they are not screened for potential anticompetitive outcomes[41]. However, several of these transactions affect local markets, and in several cases they are mergers to duopoly or even monopoly in the relevant product markets. This work intends to show that such mergers can have a significant effect on the whole economy, and ultimately on inequality.

This identification strategy can be implemented by considering both the number of Stealth Horizontal Mergers and Stealth Non-Horizontal Mergers as known factors. Then one can use the number of Stealth Non-Horizontal Mergers (NH_t) as a control for the number of Stealth Horizontal Mergers (H_t). In practice this amounts to constructing a vector containing the two variables and the static factors $FF_t = (F_t, NH_t, H_t)$

[39] Using a measure of market power external to the model is reminiscent of narrative identification methods used in empirical VAR on monetary and fiscal policy (see Romer and Romer (2010) for example).

[40] The US competition authorities recognize the possible anticompetitive nature of horizontal transactions. So much so that they have formally tiled their merger evaluation procedures "Horizontal Merger Guidelines".

[41] Due to their size, these mergers are considered to be harmless by the Hart-Scott-Rodino Act.

and running a VECM on this vector[42]. As a consequence the Impulse Response Functions will be:

$$IRF^{VECM} = \left[\hat{A}^{VECM}(L)\right]^{-1} R \qquad \text{for M\&A Deals}$$
$$IRF^{FECM} = \hat{\Lambda} \left[\hat{A}^{VECM}(L)\right]^{-1} R \qquad \text{for all other variables}$$

Where the identification matrix R is the Cholesky factor of the covariance matrix of residuals:

$$R = chol(u_t u_t') = \begin{bmatrix} x_{11} & 0 & 0 & \dots & 0 \\ x_{21} & x_{22} & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{r1} & x_{r2} & x_{r3} & \dots & x_{rr} \end{bmatrix}$$

This identification scheme relies on imposing restrictions on the contemporaneous response of certain variables to the identified shocks. In particular the researcher imposes zero restrictions, which imply some variables do not react contemporaneously to some shocks. Each row of the rotation matrix R corresponds to a variable, while each column corresponds to a shock. The last column of the matrix describes the identified market power shock, which is defined as the shock that affects only the number of Stealth Horizontal Mergers H_t contemporaneously. All zeros in the last column represent the fact that no variable other than H_t responds contemporaneously to the identified shock. As a consequence all other variables will react in the subsequent periods in response to movements in H_t caused by the shock itself.

$$H_t = h_m + \alpha_{1,m} NH_t + \alpha_{2,m} F_t + \beta_m H_{t-1} + \gamma_m NH_{t-1} + \delta_m F_{t-1} + ... + \underbrace{u_{1,t} + u_{2,t} + ... + u_{M,t}}_{\epsilon_t} \tag{3}$$

The last row of R describes the crucial equation for identification of the market power shock, the equation of Horizontal M&A Activity as described in (3). This identification structure allows to decompose the residual ϵ_t into several shocks $u_{i,t}$. The market power shock $u_{M,t}$ is part of the residual of a regression of current H_t on current NH_t, the factors F_t and past variables. One can then interpret the shock $u_{M,t}$ as the part of Horizontal $M\&A$ Activity which is not explained by Non Horizontal $M\&A$ Activity or other shocks in the economy, with the addition of further controls in the form of past realizations of $M\&A$ variables and all other variables represented by the factors F. The presence of other shocks $u_{1,t}, ..., u_{8,t}$ in the equations ensures that the identified market power shock $u_{M,t}$ is not capturing other sources of variation, such as technology shocks[43]. Therefore this shock represents unexpected and unforcastable variations in the number

[42] The linear equations of this VECM can be described by:

$$G(L)\Delta FF_t = h + \alpha\beta' FF_{t-1} + Ru_t$$

[43] The identified shock $u_{M,t}$ is orthogonal to all other shocks $u_{1,t}, ..., u_{8,t}$ identified in this model. This is a property fo Cholesky identification schemes.

of horizontal mergers. An example of such exogenous variations is the Amendment to the Hart-Scott-Rodino Act of December 2000, which raised the number of horizontal mergers by about 320 per year, as it is shown by Wollmann (2019). This methodology in a FAVAR setting has been already applied in the literature, as one can see from the identification of an uncertainty shock in De Giorgi and Gambetti (2017), and it can be applied also in a Factor Vector Error Correction setting.

3.2.2 Discussion

This identification strategy exploits exogenous variations in M&A activity over the whole sample and correlates them with all variables in the dataset, so as to infer their effects on the whole economy. One then might ask: there is a readily available exogenous change, the Amendment of December 2000, why not use that as an identification device? Why not use a Diff-in-Diff methodology such as Wollmann (2019)? In order to apply such identification strategy to income inequality, one would need to devise a control and a treatment group, dividing the population in those that are affected by the Amendment and those that are not. Unfortunately this is not possible because census data on households provides no information regarding the company or the sector in which interviewed people are employed. Moreover, there is no information regarding the type of assets held by these households.

An exogenous increase in the number horizontal mergers raises concentration and market power, and as a consequence it increase profits for owners of affected companies and decreases earnings for workers. Unfortunately it is not possible to identify such owners and workers, and therefore it is not possible to devise a treatment and a control group. Instead, this work identifies a series of exogenous changes in M&A activity and shows what effect they have on the whole households distribution of earnings and income, and ultimately on inequality. This identification is clearly weaker than an event study which exploits the Amendment, but it is a way to leverage the whole time series and the large dimensional dataset to overcome limitations in the data.

Given the aforementioned limitations, this work cannot directly infer the effects of the Amendment. This antitrust policy change provides an important source of variation, though. Indeed the identified market power shock is affected by the Amendment, especially in the first quarter of 2001 and then in the years following it. This work, however, can only infer the effects of an exogenous change in the number of Stealth Horizontal M&A, which is what followed the Amendment in December 2000.

One of the main concerns regarding the identified shock is that it is not capturing an increase in market power, but something else. Part of the increase in markups that is documented in the recent literature has

been explained by technological changes[44]. These changes are likely to affect also the market structure, and thus firms' incentive to merge. On the other hand, they can also be linked with income inequality. Therefore, one is lead to think that technological changes could explain the co-movement of markups, mergers and inequality. The identified shock, however, captures a change in the number of horizontal mergers with respect to non-horizontal ones. Therefore, it is not enough that the proposed technological change affects merger incentives. It should also affect horizontal mergers differently with respect to non-horizontal ones, which act as a control for overall merger activity.

Alternatively, the identified shock might be capturing horizontal mergers reacting to changes in non-horizontal ones. In particular, a reduction in non-horizontal merger activity might provide incentive for more horizontal transactions. If this were the case, then the identified shock would not capture stealth merger activity, but exactly the opposite: standard merger activity. In equation (3) that identifies the shock, however, the lagged term NH_{t-1} ensures that the shock is not driven by past realizations of non-horizontal mergers. This alternative explanation could hold only if horizontal mergers reacted to non-horizontal ones within one quarter[45], which is quite unrealistic.

With regard to other macroeconomic shocks that might be driving the results, the Cholesky identification strategy comes into play. The residual ϵ_t of equation (3) is decomposed into orthogonal shocks $u_{1,t}, ..., u_{M,t}$. Out of these, shocks $u_{1,t}, ..., u_{7,t}$ are the ones affecting the factors contemporaneously, and thus they represent any macroeconomic shock driving all variables represented by the factors. Since factors F_t are a good approximation of all the information available in the system, these shocks capture any movement other than merger activity. This is captured by $u_{8,t}$, which is the shock affecting only horizontal and non-horizontal mergers contemporaneously. The last one, $u_{M,t}$, is the identified market power shock affecting only horizontal mergers, which is residual with respect to all the others[46].

The properties of the factors allow to answer a further concern regarding the identification equation (3): omitted variable bias. There are many determinants of inequality, and market power is just one of them. Therefore one might think that some key variables explaining the evolution of inequality are missing from equation (3). As explained before, however, factors are meant to represent all available information in the economy, and thus they account for any possible variation that might drive explained variables. As an example one could take outsourcing to lower-wage countries, which is likely to increase inequality by compressing unskilled labor earnings. The dataset from which factors are built contains all components of GDP including export and import balance, industrial production by product category, as well as labor market indicators such as unemployment and number of employed by industry. These variables, and the

[44] I will not go into details regarding such changes, so as to leave the argument as broad as possible

[45] The frequency of the data is quarterly. This argument would be stronger if one were using yearly data.

[46] Morever, the shock $u_{M,t}$ is orthogonal to all the other shocks

relative factors, carry the information representing the process of outsourcing. Therefore, the factors F_t act as an effective control for outsourcing to lower-wage countries.

4 Results

The main results of this work concern the identification strategy based on shocks to M&A Deals. Variations of such identification strategy, as well as the identification strategy based on sign restrictions are included in the robustness section.

4.1 Main Results

In order to better understand the identified shocks to M&A Deals, it is useful to inspect its effect on some relevant macroeconomic variables. The first panel of Figure 1 shows that the shock has a positive and long lasting effect on the number of Stealth Horizontal M&A deals. With regard to the size of the shock, standard procedure in the literature is to set the shock equal to the standard deviation of the relevant variable[47]. An alternative, and more conservative procedure, is to use the size of a known exogenous shock. Wollmann (2019) estimates that the Amendment increased the number of Horizontal Mergers by about 3200 mergers in 10 years. Such an effect can be attained with a shock of about 40 mergers, which will be the normalization used for the following results. This shock, however, cannot be interpreted as the direct effect of the Amendment, but simply as the effect of an exogenous occurrence of 40 Stealth Horizontal Mergers. The identified shock is self reinforcing, and it is strongly persistent, as one can see from the first panel of Figure 1. This persistence will then drive most of the long run results of this work.

The shock has a negative and significant effect on the GDP, as one would expect after an increase in market power[48]. The negative impact on GDP ensures that the shock is not identifying a merger wave which is due to favorable economic conditions. About five years after the shock, its effect on output become positive, which can mean that mergers eventually result in an increase in output, but require a long time to realize efficiency gains that offset increases in market power. The third panel of Figure 1 shows that the share of output that goes to profit responds positively in the long run. On impact it does not move much, but it increases steadily after one year. In particular the shock raises the profit share by about 1% in the long run. Unemployment follows a path that is specular with respect to the one of GDP. When the shock

[47]In this case, the standard deviation is about 65 mergers per quarter.

[48]GDP is measured in log points, so the effect of the shock is to reduce GDP by as much as 3% in tow years after the shock hits the economy.

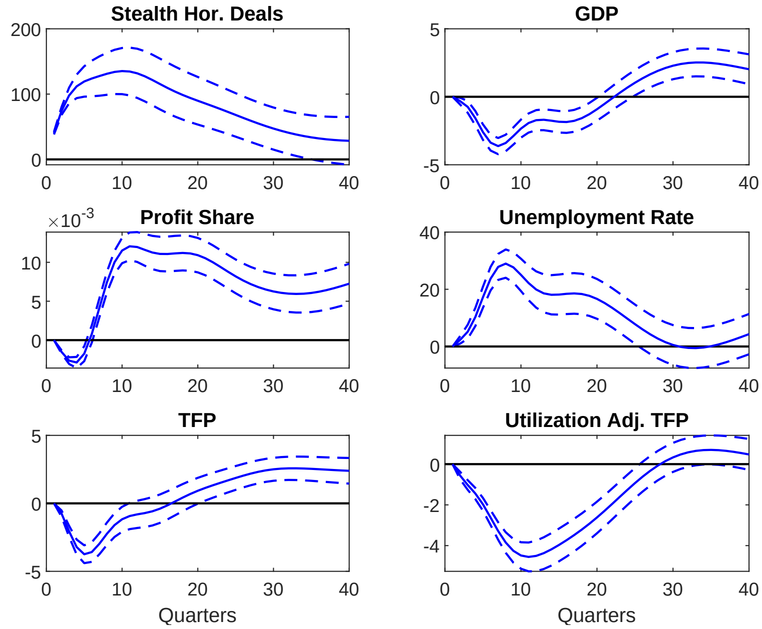


Figure 1: Impulse Response Function of macro variables to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.

hits, there is an increase in unemployment[49]. However, following the increase in output, the positive effect on unemployment becomes smaller and eventually non-significant.

As a way to get further insights into possible merger efficiencies resulting from the identified shock, one can inspect the IRF of Total Factor Productivity (TFP). From Figure 1 it is clear that TFP follows a path that is very similar to the one of GDP, decreasing in the short run and increasing afterwards. This provides further evidence that merger efficiencies take several years to realize. The conclusion changes, however, if one looks at utilization adjusted TFP (last panel of Figure 1). If one takes into account the change in utilization of factors of production, the negative effect on productivity is even stronger, and it never turns significantly positive[50]. Therefore the output increase in the long run is due to the use of spare capacity rather than productivity gains. These results show that antitrust policy should consider not only contemporaneous effects of mergers, but also its effects in the years following the transactions, as efficiencies do not realize immediately.

One key measure of market power is firm level markup. A shock to market power is expected to increase

[49]Unemployment is still computed in log points

[50]Such a negative impact on productivity is in accordance with the previous result of Blonigen and Pierce (2016), who show that mergers increase markups without generating productivity gains.

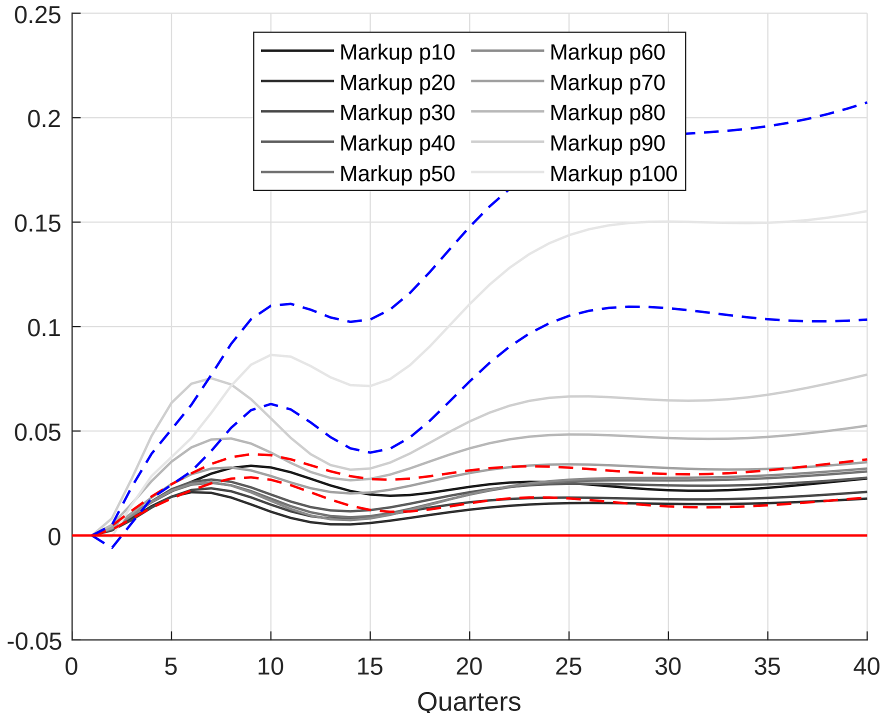


Figure 2: Impulse Response Function of the distribution of firms markups to a shock of M&A Deals. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.

markups, and Figure 2 shows the response of markup distribution. In this figure, IRF of all 10 deciles are reported, so as to appreciate the eventual spreading of the distribution in response to the shock. Color grading starts with darker lines for the lower deciles and lighter lines for the upper ones. Confidence bands are reported only for the 1st and 10th deciles, so as to give an impression of the overall significance, without creating too much visual noise. As one can clearly see, the response is positive for all deciles both in the short and in the long run. As a consequence the entire distribution of markups is shifting upward. But this is not all, the shape of the distribution is changing, as the upper end of the distribution is more responsive to the shock than the lower deciles[51]. Firms in the top decile increase their markup by 15% in the long run, while firms in the lower deciles increase it by less than 2%. The result of Figure 2 implies that markups are increasing after a shock to the number of horizontal M&A Deals, and the distribution of markups is spreading and becoming more unequal.

Once the shock to M&A has been described and characterized, one can study its effects on households

[51] This result agrees with De Loecker, Eeckhout, and Unger (2020), who observe that the upper end of markups distribution explains a large portion of the variation of markups, and thus it is the one that is driving the recent increase in average markups.

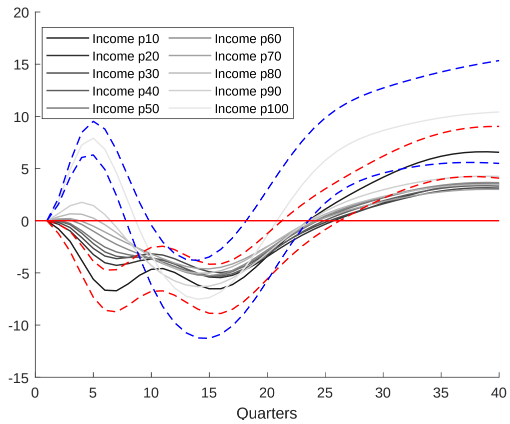
inequality. Figure 3 shows the response of distributions of Income and Earnings, as well as the response of these variables by education groups. Starting from Figure 3a, the IRF of Income, one can clearly see that most of the distribution is loosing income after the shock, apart from the highest deciles which shows a significant gain in income both in the short and in the long run. One particular feature of this figure is the ordering of the IRF. Lower deciles, the poor, loose more income than the rich, and the ordering of deciles is almost perfectly preserved. This can be clearly interpreted as an increase in income inequity, driven mainly by losses suffered by the poor. The income distribution spreads substantially in the short run, in the first two to five years, but the effect of the shock can be seen also in the long run, when the income distribution shifts upward, driven likely by the increase in GDP. Still, the upper end of the distribution is gaining almost 10% of income, more than the lower end, generating permanent changes in inequality. Figure 3c shows the response of income by education categories. Again, the disadvantaged are loosing more than the College educated in the short run. In the long run, however, there is no significant difference in the two responses.

Figure 3b shows response of the distribution of Labor Earnings. The overall pattern is similar to the response of income, since most of households income is composed by labor earnings. Earnings are substantially decreasing after the shock, and the poor are affected the most[52]. The richest gain both in the short and in the long run. Again, one can see a clear ordering of earning deciles responses, meaning the richer households are gaining more from the shock than poorer households, contributing to increasing inequality. A similar picture is drawn in Figure 3d, where one can see that the different response of college educated and non-college educated can explain some portion of the difference in earning deciles only in the short run.

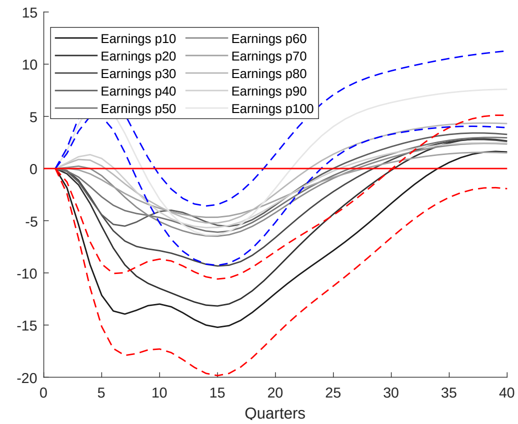
Another way to study the effect of a market power shock is to inspect the responses of standard measures of inequality, such as Gini Indexes. This serves also as a robustness check on previous results, since Gini coefficients are computed on the same disaggregated data, but their response to a shock is not the same as Gini index computed on responses of deciles. Figure 4 shows IRF for Gini coefficients, and clearly it implies that the identified shock increases inequality. This is true for both income and earnings in the short run, where the sharp increase in Gini indexes for income and earnings mirrors the dynamics of their distributions. After a rapid increase in the first two years, the effect on income and earnings inequality is persistent, and remains significant in the long run. It is worth stressing again that IRFs of Gini indexes are perfectly consistent with IRFs of income and earnings deciles, providing further support to previous results. This feature does not arise by construction[53]. Their coordinated response, then, is a clear sign that a shock to market power does increase income inequality, and this change is a long lasting one.

[52]the lowest decile looses 15% of earnings in the short run

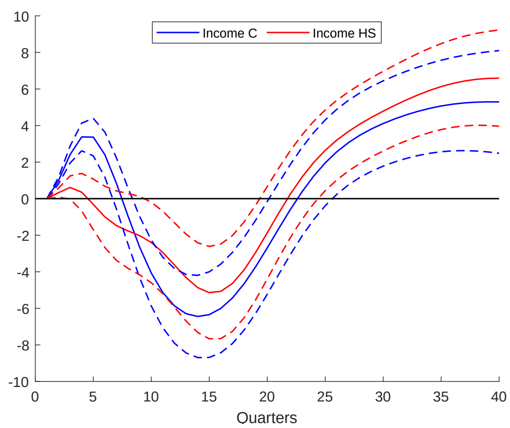
[53]All these variables are part of the dataset and are driven by the same factors, but with variable specific factor loadings.



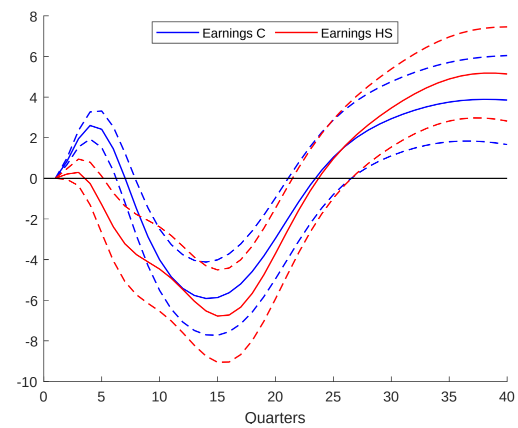
(a) Income by Deciles



(b) Labor Earnings by Deciles



(c) Income by Education



(d) Earnings by Education

Figure 3: Impulse Response Function of the distribution of Hoouseholds variables to a shock to M&A Deals. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.

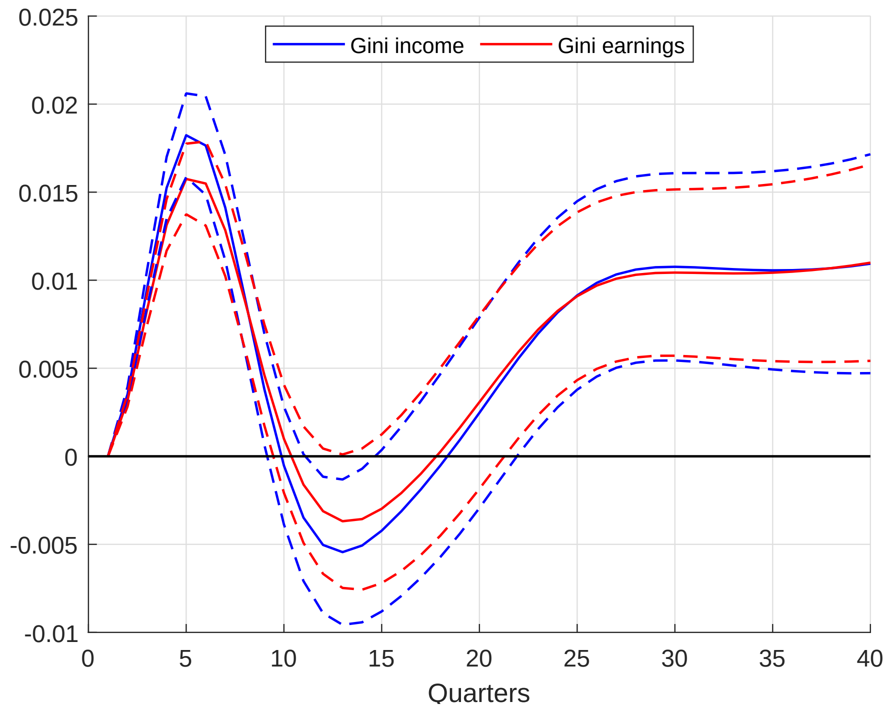


Figure 4: Impulse Response Function of Gini index for Income, Earnings and Consumption to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.

4.1.1 Relevance of the identified shock

With regard to the magnitude of the increase in inequality, one can see from Figure 4 that after about one year the shock generates an increase of about 1.5 Gini points for income, while in the long run the shock increases income by 1 Gini point. This is the simulated effect of an exogenous occurrence of 40 Stealth Horizontal M&A. To put things in perspective, the data show a Gini index for household income of about 38.6 for 2001Q1, which implies that a shock of this size can increase Gini index for income by about 2.5% in the long run.

Another insightful way to assess the magnitude of the identified market power shock is Error Variance Decomposition[54]. From Figure 5 one can see that the market power shock is an important driver of income and earnings Gini index in the long run, accounting for roughly 20% of their common component variance.

[54] This exercise decomposes the forecasting error variance for the common component of each variable in the portion that is explained by each shock. Red bars represent the portion explained by the identified shock to M&A, while green bars represent the portion explained by the shock driving the variable that is used as main control in the identification equation, that is the number of Stealth Non-Horizontal Mergers. Blue bars represent all the other shocks moving the economy, which are not of particular interest for this analysis.

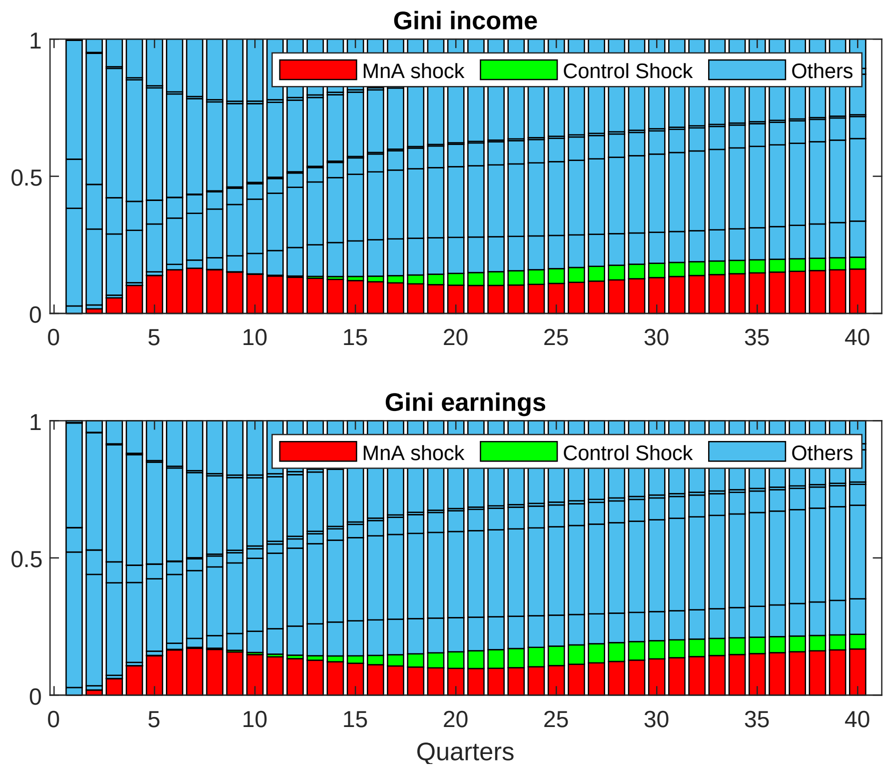


Figure 5: Error Variance Decomposition of the common component of several variables. The shock of interest is the M&A Shock, represented by red bars. The other shocks are the ones driving factors and thus the rest of the variables in the dataset

Moreover, is the most relevant component of variance of horizontal M&A Deals, and it is a significant driver of both GDP and profit share, especially in the long run[55].

A further way to quantify the effect of the market power shock is to construct an historical decomposition[56]. Figure 6 shows the historical decomposition of Gini Index for Income. The variable is centered, so that the level of the vertical axes is not relevant. The scale is preserved, though, meaning that Gini Index increased by roughly 2 Gini points from 2001Q1 to 2006Q4. The red line shows that the common component of the model, what the whole model can explain, accounts for most of the increase in Gini income. This ensures that the model is capturing most of inequality variation. The common component is the sum of various pieces, including the contribution of each shock. The purple line shows the contribution of the identified market power shock, and it is clear that the shock contributed to an increase of about 0.4 Gini

[55]In particular the makret power shock can explain about 30% of profit share variation.

[56]This exercise consists in decomposing a variable in the parts that are explained by the various pieces of the model, and in particular the parts explained by each identified shock. This procedure is applied only on the common component of the variables, which is reported in red.

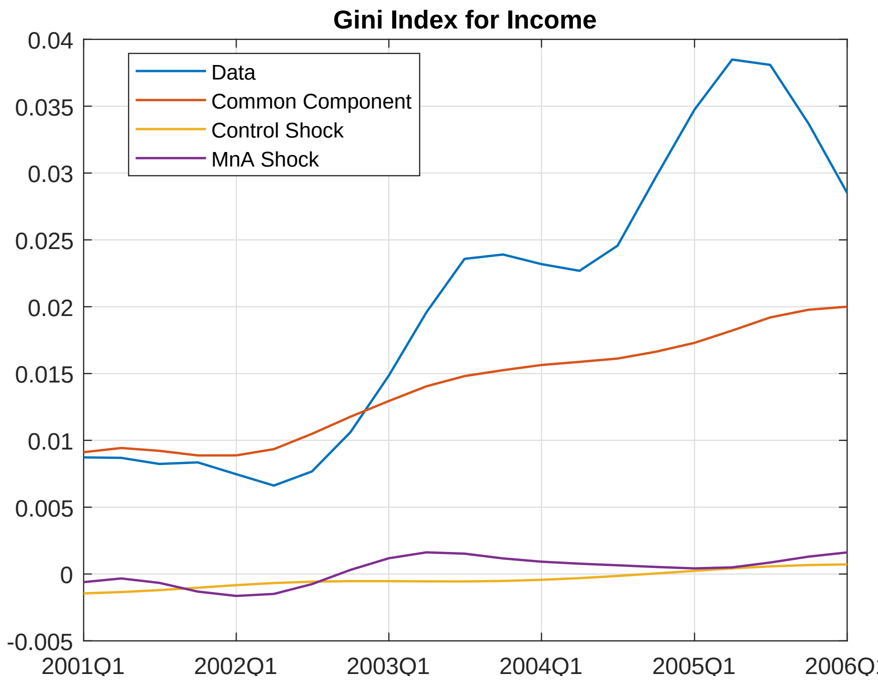


Figure 6: Historical Decomposition of Gini Index for household income. The variable is centered, so that the level of the vertical axes is not relevant. The scale is preserved, though, meaning that Gini Index increased by roughly 2 Gini points from 199Q1 to 2006Q4. Common Component represents the portion of the variable which is explained by the model, while M&A Shock represent the portion of the variable which is explained by the identified shock.

points in the five subsequent years after 2001.

4.1.2 Industry level analysis

In order to further understand the channels through which the identified shock to market power propagates to the whole economy, one can assess the effects that it had on each industry. This analysis, given its very nature, can only comprise industry level variables, as it is not possible to relate a certain part of the population to a single industry. Therefore this section will focus on merger activity and markups level within each industry[57].

This analysis comprises 23 industries with enough firms and merger activity. For each industry the number of Stealth Horizontal M&A deals and the average markup are added to the dataset[58]. The response

[57]Industries are defined as two-digit NAICS levels, so as to have enough mergers in each quarter to generate variation and so as to have enough firms in each industry to compute reliable measures of markups.

[58]With regard to the identification strategy, these industry level variables play the role of additional controls driven by the

of other variables does not change significantly, and the same goes for the main results presented until now. Figure 7 shows the impulse response function of M&A Deals and markups in each industry. In 20 industries out of 23 the number of horizontal M&A increases as a consequence of the shock, showing that the identified market power shock generates increases in concentration across the whole economy[59]. On top of that, in 15 industries out of 23 the response of markups tracks the response of M&A Deals, showing that the two series move in the same direction following the shock. An example could be Mining, Quarrying, and Oil and Gas Extraction, a sector in which the shock generated an increase of about 3 mergers per quarter and an increase of about 0.1 in markups. Six industries out of 23 show an inverse pattern, where M&A Activity and markups respond in opposite directions[60]. All these industries show an increase in the number of M&A but a decrease in markups[61].

Further inquiry into the reasons behind different industry dynamics is beyond the scope of this work. This section is meant to provide evidence on the fact that macroeconomic trends deriving from the identified market power shock can still be found in a large portion of US industries. In particular, the shock generated an increase in the number of horizontal M&A deeals, concentrating these industries, and it raised industry level markups. As a consequence the identified shock made these industries more concentrated, less competitive and more profitable.

factors.

[59]Notable exemptions are Non-Metal Manufacturing; Professional, Scientific, and Technical Services; and Other Services, except Public Administration.

[60]This is the case for Utilities, industry NAICS 44 and 45 (Retail Trade), Transportation and Information.

[61]In a similar way, Other Services saw an increase in markups and a decrease in M&A activity in the short run, but then in the long run markups decreased, following M&A actovity.

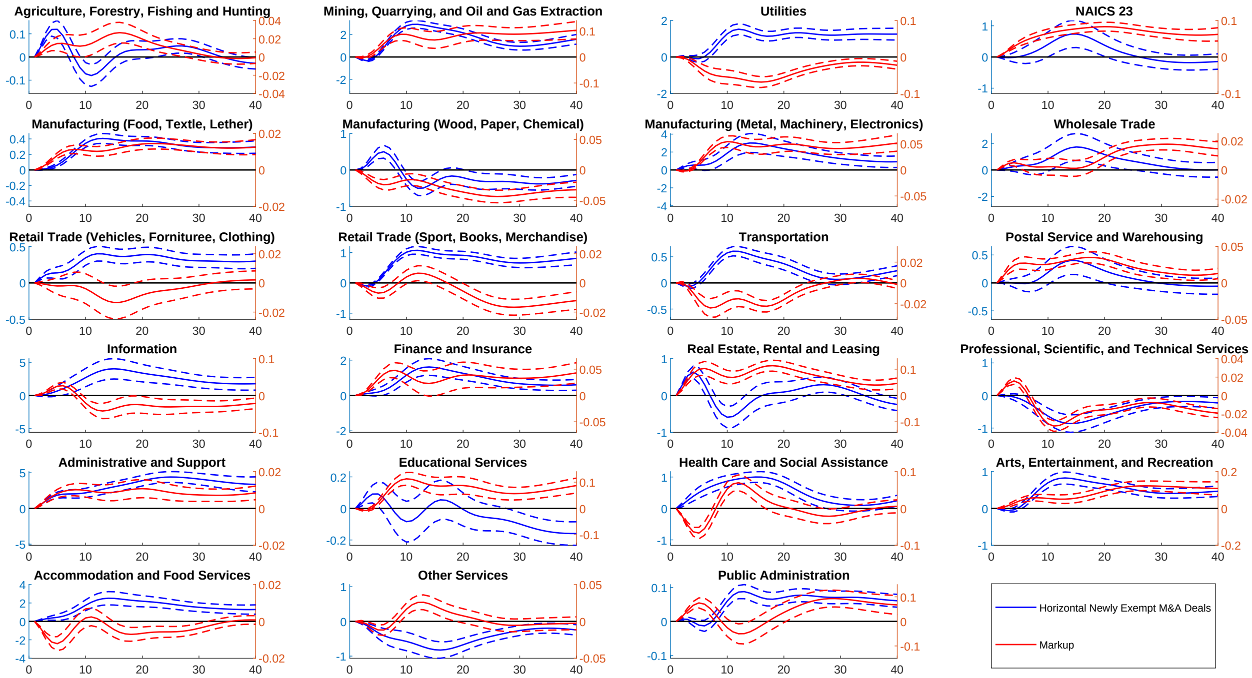


Figure 7: Industry level Impulse Response Function of Horizontal Newly Exempt M&A Deals and Markups to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.

4.2 Robustness

The first kind of robustness analysis that needs to be performed with a Cholesky identification strategy concerns the ordering of variables used in the recursive scheme[62]. It can be argued that the ordering chosen for the main result is the one imposing more stringent restrictions on the desired shocks, since a zero restriction are imposed on the instantaneous responses of all variables except H_t[63]. A radically different ordering would require M&A Deals to be ordered first, so that the VECM is run on the vector $FF_t = (NH_t, H_t, F_t)$[64]. This identification ordering is usually employed for "slow moving" variables, such as technology, since it implies that the identified shock is the only one affecting M&A instantaneously. As a matter of fact, this identification scheme does not require that all variables, through the factors, act as controls in the equation for H_t, where the shock of interest is $u_{M,t}$.

$$H_t = h_m + \alpha_{1,m} NH_t + \beta_m H_{t-1} + \gamma_m NH_{t-1} + \delta_m F_{t-1} + ... + u_{1,t} + u_{M,t}$$

[62] It is well known that such identification produces orthogonalized shocks that are easy to interpret, but it is often required that results are robust to different orderings of relevant variables.

[63] As a consequence the identified shock affects H_t contemporaneously, but it cannot affect other variables.

[64] In this case the shock of interest is the one pertaining to the second column of the Cholesky matrix R.

Figure 12 in the Appendix shows that the response of macroeconomic variables does not change much with respect to the previous identification strategy, especially in the long run. The response of markups does not change as well, as one can see from Figure 13 in the Appendix. The response of income and earnings distributions is not appreciably different, supporting the same patterns of the main results. Lastly, Figure 14 shows the IRF of Gini indexes, similarly to the ones reported in Figure 4. Patterns agree in the two figures, and noticeably the magnitude of the responses do not change, showing that conditioning on more variables does not affect the main result. The same goes for the historical decomposition, as one can see from Figure 15 in the Appendix.

One then could use different variables to measure M&A activity. Unfortunately the dataset provided by Thompson and Reuters lacks information regarding transaction values and firms assets for the majority of M&As. As a consequence a shock identified by using these measures is to be considered less reliable. Nevertheless in the Appendix one can find IRF for a shock identified using M&A Deal Value, rather than the number of Deals. As one can see from Figure 16 in the Appendix, the effect of a shock identified using all M&A deals has a similar effect on macroeconomic variables. The shock, however, is not calibrated, so that it is not possible to make considerations on its magnitude. Regardless, this shock has a similar effect on markups (Figure 17) and on Gini indexes (Figure 18).

A further sensitivity check can be performed by changing the way firm markups are computed. As explained in Appendix A, firm level markups are computed following the methodology of De Loecker and Warzynski (2012) and accommodating for the presence of fixed costs[65]. Figure 19 in the Appendix shows that response of macroeconomic variables does not change substantially, with the exception of TFP, which ramains always positive. Utilization adjusted TFP decreases in response to the shock, though. Markups estimated without fixed costs increase after the shock, as shown in Figure 20. The same can be said for Income and Earnings Gini Indexes (Figure 21). An even less refined measure of markups is given by the Lerner Index[66]. Results computed employing this measure do not differ substantially woth the main result, and are not reported here.

Rather than changing a controlling variable, one could change the variables that are used to identify the shock. One could simply use the number of Horizontal M&A Deals as identifying variable, and GDP as control. The resulting equation would be:

$$H_t = h_m + \alpha_{1,m} GDP_t + \alpha_{2,m} F_t + \beta_m H_{t-1} + \gamma_m GDP_{t-1} + \delta_m F_{t-1} + ... + u_{1,t} + ... + u_{M,t}$$

This strategy allows to identify a M&A wave which is not justified by favorable economic conditions, as GDP

[65]De Loecker, Eeckhout and Unger (2020) show that markups computed without accounting for fixed costs are significantly higher.

[66]Which is nothing more than the ration between $(P - MC)$ and the price P, and it can be computed at the firm level.

is assumed to not respond contemporaneously to the shock by construction. Figure 22 in the Appendix shows that this is the case, and that other variables respond similarly to the main result. The main difference is in the scale of the response, as an increase of 3200 Horizontal Deals is less relevant than an increase of 3200 Stealth Horizontal Deals[67]. Notwithstanding the scale of the IRF, the response of markups and Gini index are very similar to the main results, as one can see from Figure 23 and Figure 24. This shows that not only Stealth Consolidations effects on inequality, but potentially any increase in horizontal mergers can. As a consequence the results of this paper extend also to larger M&A transactions.

Rather than a standard recursive identification procedure, one could try a more agnostic one based on Antolín-Díaz and Rubio-Ramírez (2018) Narraive Sign Restrictions[68]. The response of macroeconomic variables was calibrated in the same way as the main result, so as to make them comparable. Such impulse responses of macroeconomic variables can be seen in Figure 25. Similarly to the shock to M&A deals, the response of GDP is negative only in the short run, and it turns positive afterwards. Unemployment mirrors the path of GDP, increasing in the short run and decreasing afterwards, so as to accommodate the increase in output. Total factor productivity decreases in the short run, explaining the pattern of GDP.

The response of markup distribution is again similar to the one observed to the shock to M&A Deals (Figure 26), with the high end of the distribution clearly increasing more than the lower end. Figure 27 shows the response of income and earnings distributions. The pattern of these variables shows a remarkable similarity with the main results, but confidence bands show less significance in the long run. Nonetheless, the response of inequality, as measured from Gini indexes, is positive both in the short and in the long run, as one can see from Figure 8, and with a magnitude that is similar to the main result. Furthermore the error variance decomposition shows that the shock identified with sign restrictions explain about 50% of the forecast error variance of income Gini index[69]. Overall, results from this alternative Sign Restriction scheme support the main ones, showing that a shock to market power identified with M&A Activity has a significant and long-lasting effect on income inequality.

[67] This is merely due to the fact that Stealth Deals are a subset of all Deals.

[68] Such identification scheme relies on imposing restrictions on the sign of impulse responses of certain variables, as well as the historical decomposition of those variables, and it is explained in Appendix C.

[69] The shock of interest, meaning the one on which sign restrictions are imposed, is shown in red in Figure 28.

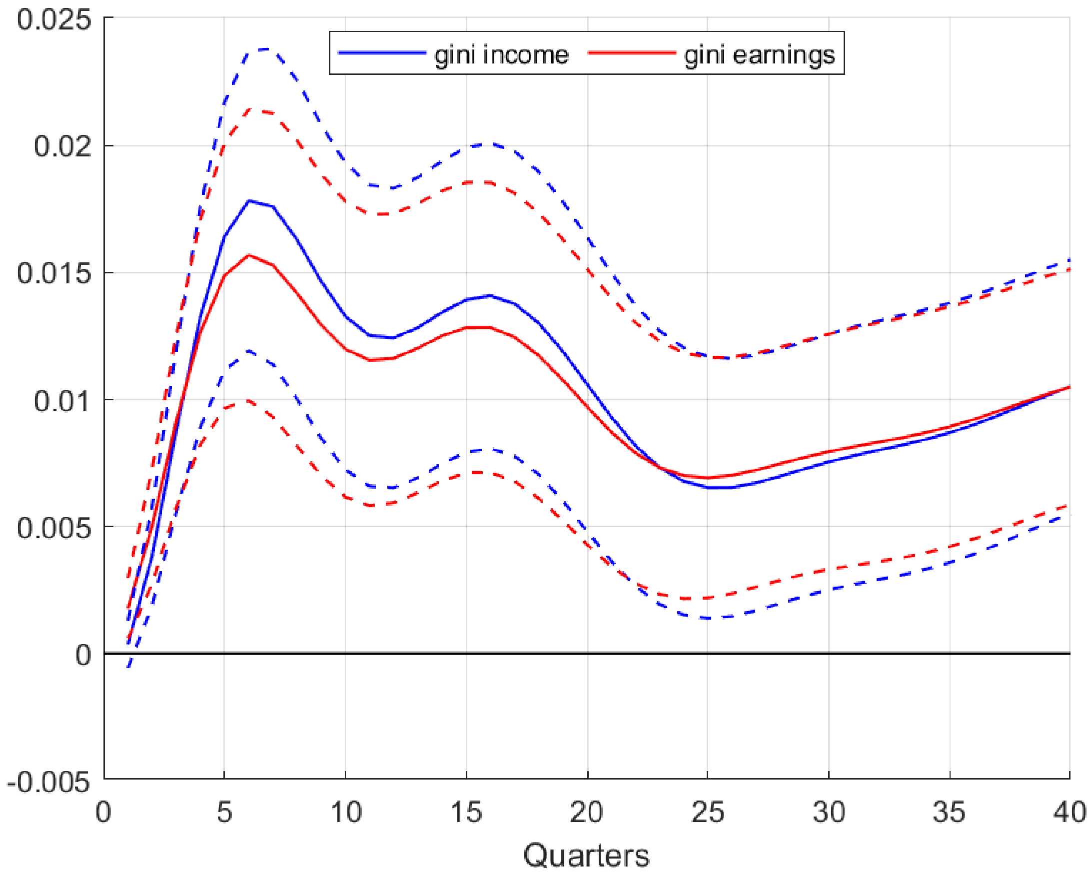


Figure 8: Impulse Responion of Gini indexes for Income and Earnings to a shock identified using Sign Restrictions. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.

5 Conclusions

Inequality has recently reached the center of political and academical debate because of the dire consequences it can have on people's life and society as a whole. It increased at an alarming rate in past decades, changing our societies dramatically. But what are the determinants of income inequality? What can explain an increase in inequality? Which mechanisms play a role in changing income distribution? This paper studies one of such mechanisms: the effect of stealth consolidation and market power on income inequality. Stealth consolidation refers to anticompetitive mergers that go under the radar of antitrust authorities due to their unassuming size. Such mergers, however, can have significant effects on market power in segmented and local

markets. Market power is the ability of firms to manipulate the market so as to increase their profits. This favors firm owners at the expenses of firm workers, and thus it has the potential to raise income inequality.

This work applies a Dynamic Factor Model to a large US dataset so as to model the whole economy and derive the effect of exogenous changes in market power. The dataset combines CEX survey data on heterogeneous households with Compustat data on heterogeneous publicly traded firms and Thompson Reuters data on M&As. It applies cointegration time series methods to such a large set of variables thanks to the Dynamic Factor Model. The shock to market power is identified by exploiting differences between horizontal stealth M&As and non-horizontal stealth M&As. This shock to market power decreases output and total factor productivity on impact. It has a positive effect on firm markups, especially for firms in the upper tail of markup distribution. The shock increases income and labor earnings inequality in the short run, and this is mainly due to an earnings loss for the poor.

In the long run the effect on output is positive, thanks to merger efficiencies that take several years to fully realize. The level of Market Power is changed permanently, thanks to the strong persistence of the shock. As a consequence the share of output that goes into profits increases in the long run. Notwithstanding an increase in output in the long run, also the effect on income and earnings inequality is permanent. The identified market power shock increases the income Gini index by 1 Gini points in the long run, or an increase of about 2.5% of income Gini. Error variance decomposition shows that the identified shock to market power accounts for 20% of the forecast error variance of Gini index in the long run. Moreover, an historical decomposition of Gini index shows that between 2001 and 2006 the identified market power shock accounted for an increase of about 0.4 Gini points.

Results of this work show how all agents in our complex societies are intertwined. Starting from the 80s, both inequality and market power began to rise, and this increase continues to this day. These trends have already been paired together countless times, so as to answer the same question of this paper: does market power increase inequality? This work shows compelling evidence of the causal effect that stealth consolidation can have on income inequality, and it provides insights into mechanisms driving this causal link.

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Appendix

Appendix A: Firm Level Markup Computation

In the framework proposed by De Loecker and Warzynski (2012) markups are estimated at the firm level using the financial data and the cost minimization problem of the firm, without imposing any assumption on the demand and type of competition. In particular, the researcher has to madel the production function of the firm:

$$Q_{it} = Q_{it}(\Omega_{it}, V_{it}, F_{it}, K_{it})$$

Where Q are sales (SALE in Compustat), V is a vector of variable inputs (COGS in Compustat), F represents fixed costs (SG&A in Compustat) and K stands for capital (PPEGT in Compustat). All variables are deflated using appropriate deflators. The index i represents firms and t stands for time. Then, given the minimization problem faced by the firm:

$$\mathcal{L}(V_{it}, F_{it}, K_{it}, \lambda_{it}) = P^V_{it} V_{it} + r_{it} K_{it} + F_{it} - \lambda_{it}(Q(.) - \bar{Q}_{it})$$

One can note that the lagrangian multiplier λ_{it} actually represents the marginal cost faced by the firm, and thus it is possible to derive an expression for the markup:

$$\mu_{it} = \frac{P_{it}}{\lambda_{it}} = \theta^v_{it} \frac{P_{it} Q_{it}}{P^V_{it} V_{it}}$$

Where θ^v_{it} is the elasticity between output Q and variabe input V. This elasticity can be computed at the sector level (in this work 2-digit NAICS) by running sector specific panel regressions with variables in logs:

$$q_{it} = \theta^v_s v_{it} + \theta^k_s k_{it} + \theta^f_s f_{it} + \omega_{it} + \epsilon_{it}$$

Where ω_{it} represents an unobserved productivity shock, and it can be estimated by running a non-parametric regression

$$q_{it} = \phi(v_{it}, k_{it}, f_{it}) + \epsilon_{it}$$

And then just defining $\omega_{it} = \phi_{it} - (\theta^v_s v_{it} + \theta^k_s k_{it} + \theta^f_s f_{it})$. Then one can model the productivity process as an AR(1):

$$\omega_{it}(\theta^v_s) = \alpha \omega_{it-1}(\theta^v_s) + \xi_{it}$$

Lastly one can impose that variable input responds to current productivity shocks, but lagged variable input does not. Together with the condition that capital and fixed costs do not respond to current shocks, this gives moment conditions to identify the desired elasticity:

$$\mathbb{E}\left[\xi_{it}(\theta^v_s)\begin{bmatrix} v_{it-1} \\ k_{it} \\ f_{it} \end{bmatrix}\right] = 0$$

Once the sector level elasticity θ_s^v is computed, one can obtain firm specific markups for every period of time.

Appendix B: Test for the number of factors and shocks

Three tests are run to determine the number of factors and shocks in the dataset. In order to determine how many static factor r to use, Table 1 shows results of Bai and Ng (2002) test. Information Criteria is known to select less factors than Panel Criteria, and the selected number of factors ranges from 5 to 8. This work uses $r = 8$, which is one factor more than the number found by Barigozzi, Lippi, and Luciani (2016). In order to determine the number of structural shocks q, Hallin and Liška (2007) test the number of diverging eigenvalues of the spectral density $\Sigma(\theta)$ of the dataset in differences Δx. The test relies on an expansing subset of the dataset, starting from a random subset of $\frac{2}{3}N$ variables and adding variables in random order until the number N is reached. This procedure can be repeated several times with different variable draws, so as to have a better understanding of the results. Table 2 reports how many times each value for q is selected by the test. From this result it is clear that the test selects a number of structural shocks $q = 3$, in accordance with most of the literature on DFMs. Barigozzi, Lippi, and Luciani (2016) apply Hallin and Liška (2007) test on the long run spectral decomposition $\Sigma(0)$, and prove that the test selects the correct number of unit roots τ as $N, T \to \infty$. Table 3 shows this test applied to the dataset used in this work. The answer of the test is not as clear-cut as the one for q. For this work it is chosen $\tau = 1$ as the number of unit roots. It is worth noting that if one uses a number $\tau = 2$, the results of this work do not change significantly.

Table 1: Number of static factors r selected by Bai and Ng (2002) test. Both standard Information Criteria and Panel Creteria are reported.

Criteria: Loss Function	IC	PC
p1	8	9
p2	7	8

Table 2: Number of structural shocks q selected by Hallin and Liška (2007) test on $\Sigma(\theta)$. The test is repeated 100 times, and for each loss function it is reported the number of times a particular q was chosen.

Loss Function:	p1	p2	p3	p4
q				
1	1.00	1.00	1.00	1.00
3	98.00	98.00	98.00	99.00
4	1.00	1.00	1.00	0.00

Table 3: Number of unit roots τ selected by Barigozzi, Lippi, and Luciani (2016) test on $\Sigma(0)$. The test is repeated 100 times, and for each loss function it is reported the number of times a particular τ was chosen.

Loss Function:	p1	p2	p3	p4
τ				
1	53.00	56.00	56.00	56.00
2	46.00	43.00	43.00	43.00
4	1.00	1.00	1.00	1.00

Defining M as the closest integer to $\frac{1}{2}T^{1/2}$, loss functions are:

$$p1 = ((M/T)^{0.5} + M^{-2} + N^{-1}) * \log\big(\min([(T/M)^{0.5}; M^2; N])\big)$$
$$p2 = (\min([(T/M)^{0.5}; M^2; N]))^{-1/2}$$
$$p3 = (\min([(T/M)^{0.5}; M^2; N]))^{-1} * \log\big(\min([(T/M)^{0.5}; M^2; N])\big)$$
$$p4 = (\min([(T/M)^{0.25}; M^2; N]))^{-1} * \log\big(\min([(T/M)^{0.25}; M^2; N])\big)$$

Appendix C: Narrative Sign Restrictions

Given the desire to identify a shock to market power, one can characterize such shock by the effect that it has on certain key variables. Similarly to the main identification strategy, one can impose that the shock raises the number of horizontal M&A Deals. On top of that, one would want that a positive shock to market power decreases output on impact, since firms will find optimal to restrict supply in favor of profits. Lastly, in order to check that firms are gaining while output is waning, the final restriction is a positive response of stock prices. All these restrictions are imposed for the first five periods. Restrictions for identification of the rotation matrix R can be derived by imposing conditions on the IRF of certain variables. Rather than imposing some contemporaneous impulse responses to be 0, a quite strong assumption, one can be more

agnostic and impose restrictions on the sign of such IRF. This approach was pioneered by Uhlig (2005) in his seminal work on sign restrictions. Given that the Amendment to the Hart-Scott-Rodino Act had such a strong effect on M&A Activity, one would like to factor this into the identification strategy. This can be done by imposing further restrictions on the historical decomposition of certain key variables. In this case, it is natural to impose that the identified shock is the main driver of horizontal M&A Deals at the date of the Amendment, the first quarter of 2001. This approach of using external information to identify the shock is akeen to narrative identification, and it was descibed and named Narrative Sign Restrictions by Antolín-Díaz and Rubio-Ramírez (2018).

The procedure in practice is quite simple, one draws a random rotation matrix R and checks whether it satisfies the desired restrictions. If this is the case, the rotation is stored, otherwise it is discarded. The extraction is repeated thousands of times, since the process is very easy to automate. Given that sign restrictions do not provide exact identification, but only set identification, an infinite set of R matrices satisfy the desired restrictions. One could look at all successful draws of R, but this work follows the methodology of Fry and Pagan (2011), who identify the rotation R^{FP} whose impulse responses are closer to the median of all successful impulse responses. Given the computationally intensive procedures involved in sign identification, it is convenient to focus on dynamic factors, rather than static factors. In practice this amounts to a double rank reduction through the matrix $\hat{K}$ that brings the rotation matrix dimension down from $r = 7$ to $q = 3$ (See Appendix B for derivation of these numbers). As a consequence the identified IRF are computed as:

$$IRF^{FECM} = \hat{\Lambda} \left[\hat{A}^{VECM}(L) \right]^{-1} \hat{K} R^{FP}$$

Appendix D: Technology Shock

In their seminal paper Galí and Rabanal (2004) define a technology shock as the only shock that has a permanent effect on labor productivity, in accordance with the previous work of Galí (1999). They identify such shock in a bivariate VAR that includes labor productivity and is hours of all persons in the nonfarm business sector. Such a VAR is driven by two shock, and the authors impose that only one of them affects labor productivity in the long run.

The Dynamic Factor Model on which this work is built allows for a much wider array of variables, still it is driven by just three shocks. As such, one can impose zero restrictions on the long run response of these shocks, so as to identify the same shock of Galí and Rabanal (2004). In particular, one can select three variables, in this case total factor productivity (TFP), total hours worked in the economy and prices. Then one can impose that two out of the three shocks driving the economy have no long run effect on TFP, while they do have it on the two other variables. The remaining shock will be the only one driving TFP in the

long run, and thus it is identified as a technology shock.

Impulse response of macroeconomic variables are shown in Figure 9, and overall they closely resemble results obtained by Galí and Rabanal (2004). A positive shock to technology has a long lasting effect on TFP and GDP. As expected total hours decrease (series HOAMS), since labor productivity increases. Quite interestingly the DFM allows to draw IRF for all variables in the system. Consumer prices, for instance, decrease after such shock (series CPIAUCSL), showing that technological efficiencies are passed down to consumers. One should note, though, that both this work and Galí and Rabanal (2004) show low levels of significance of such IRFs. This is likely due, in both cases, to the limited time series dimension of the datasets and on the large amount of parameters that need to be identified.

Figure 10 shows the response of markups to a technology shock. Overall markups increase, showing that not all efficiencies are passed down to consumers, but some part of them is retained by producers. On top of that, high markup firms seem to be the ones increasing their markup the most, in accordance with De Loecker, Eeckhout, and Unger (2020), who show that high markup firms are most reactive to macroeconomic shocks. Figure 11, on the other hand, shows the response of households distributions. A technology shock increases Income, Earnings, Consumption and Wages, as one would respect from textbook economic models. On top of that, a DFM can give a new insight: for all these variables the high income portion of the population is gaining more, while the low income part of the population enjoys less. For earnings and consumption, the lowest deciles are even loosing after such a technology shock, showing that even a technology improvement can have some downfalls for the poorest portion of the population. These results agree with the conclusions of De Giorgi and Gambetti (2017), who also analyze the effect of both a technology and an uncertainty shock on household inequality in a DFM framework.

Confidence bands are large, and thus all these results are not very significant in a statistical sense. Nevertheless, they show that even well understood economic fluctuations can have effects on household inequality.

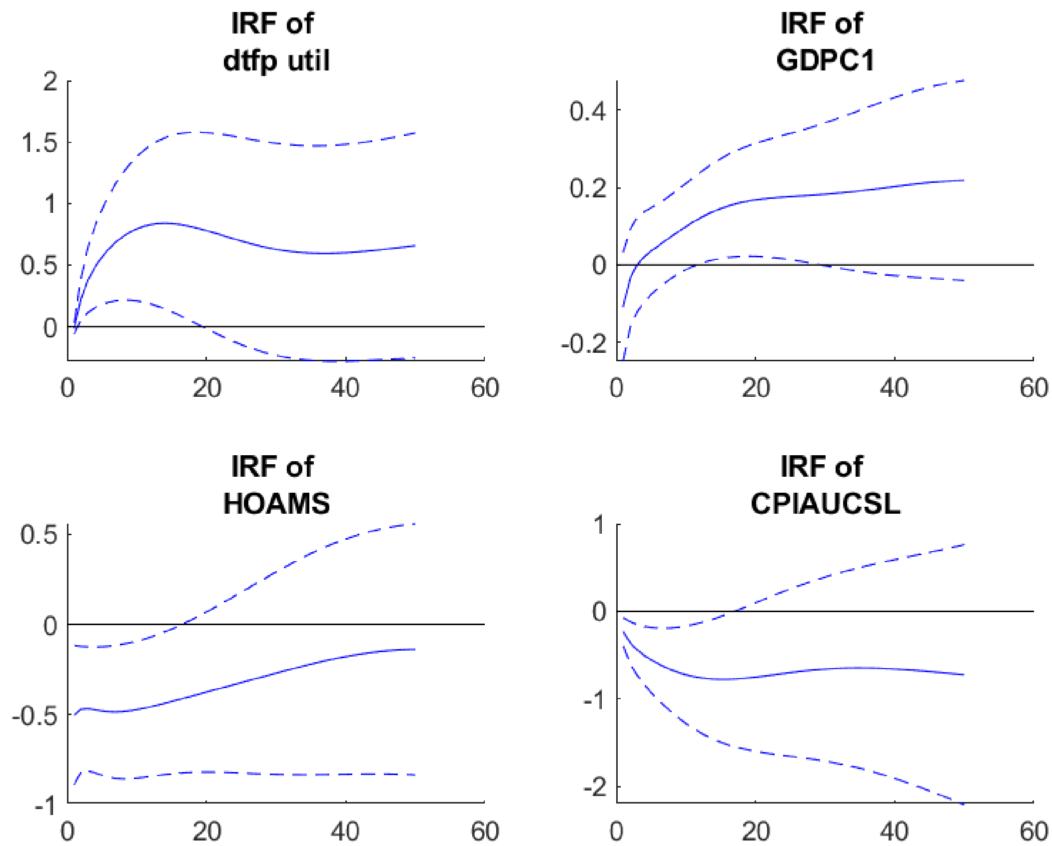


Figure 9: Impulse Response Function of macro variables to a technology shock. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

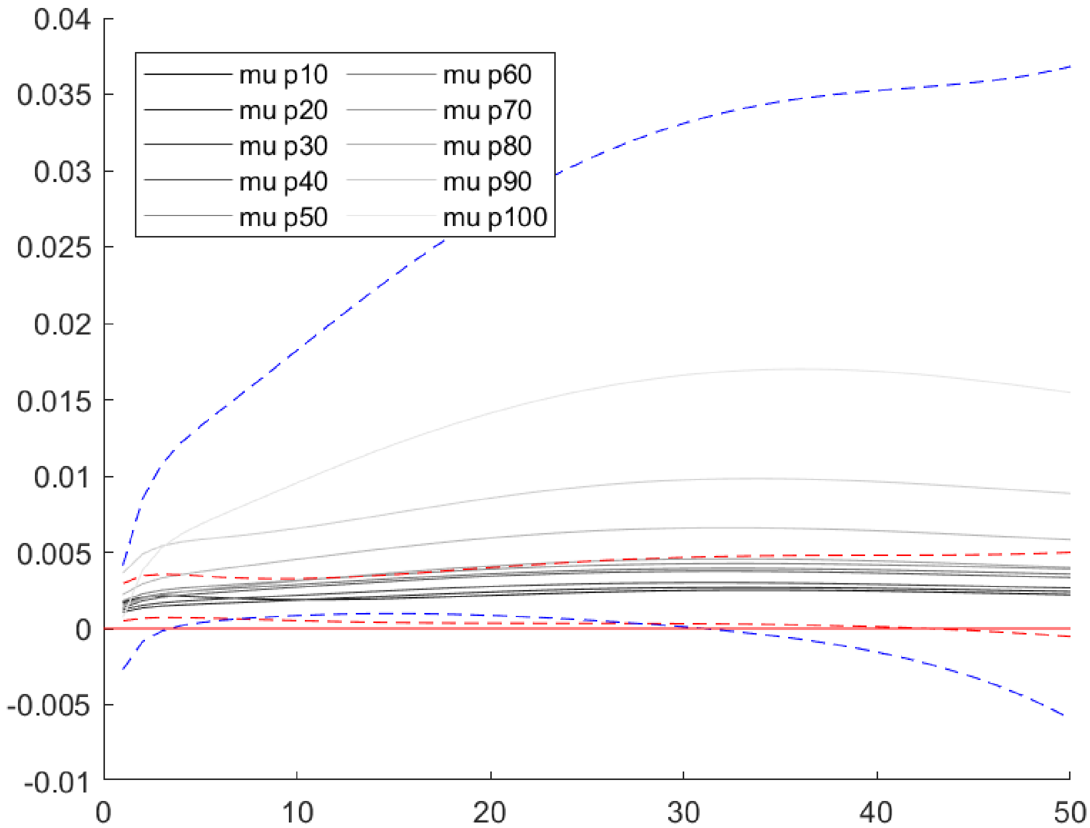
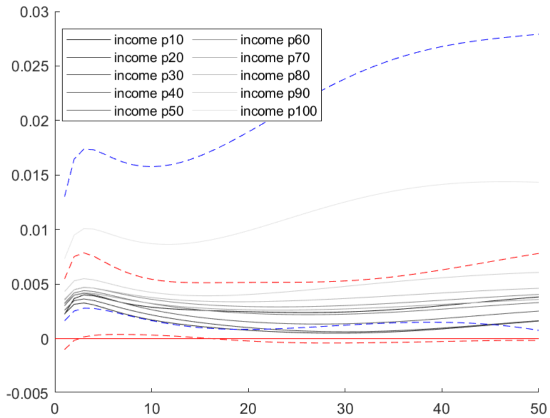
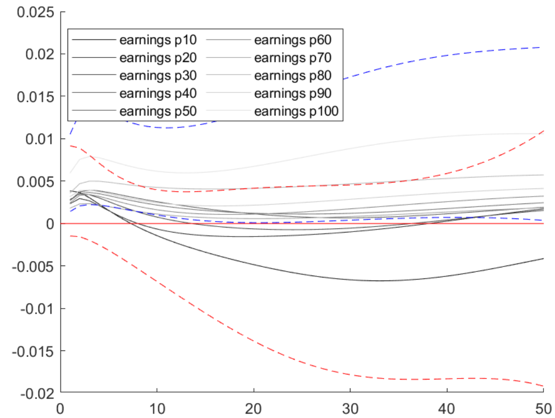


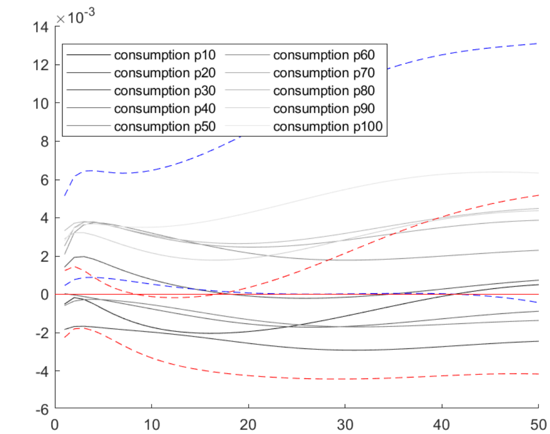
Figure 10: Impulse Response Function of the distribution of firms markups to a technology shock. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.



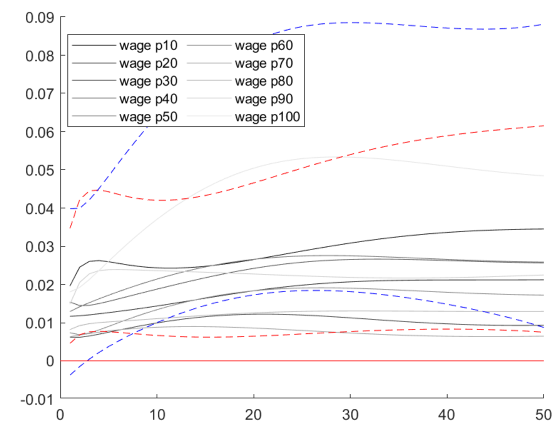
(a) Income



(b) Labor Earnings



(c) Consumption



(d) Wages

Figure 11: Impulse Response Function of the distribution of Hoouseholds variables to a technology shock. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

Appendix E: Robustness results

Different ordering in Cholesky scheme

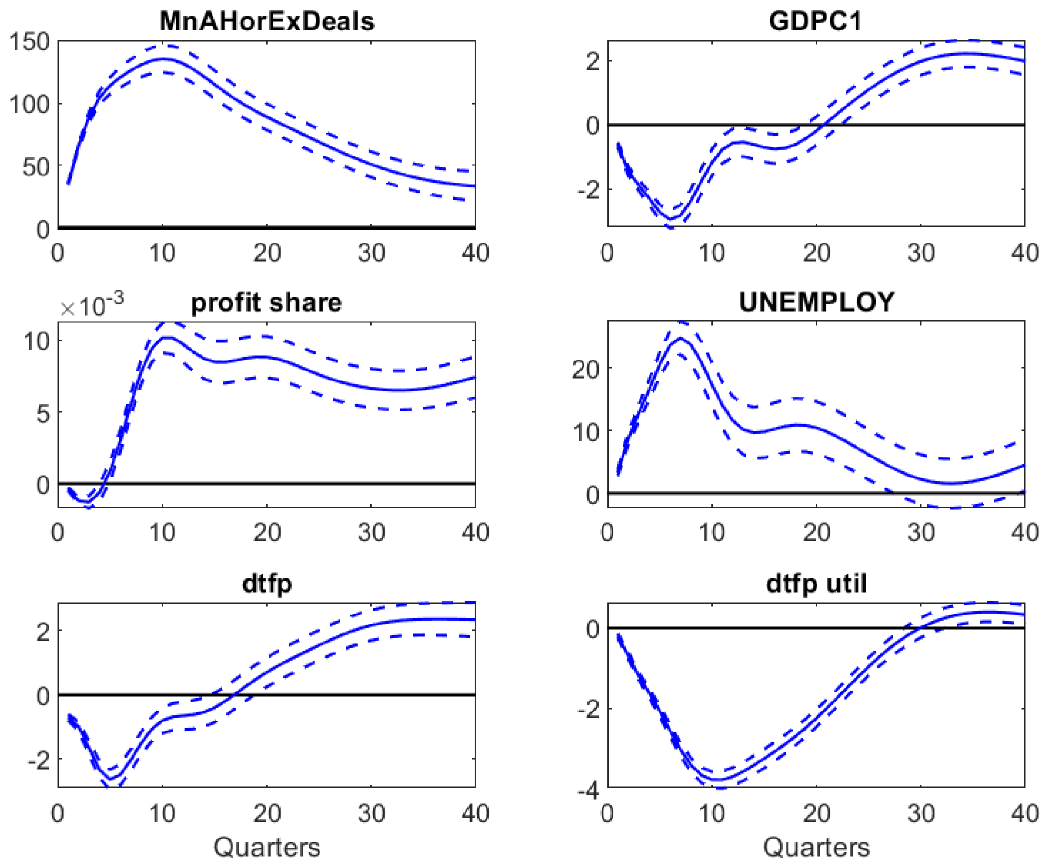


Figure 12: Impulse Response Function of macro variables to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

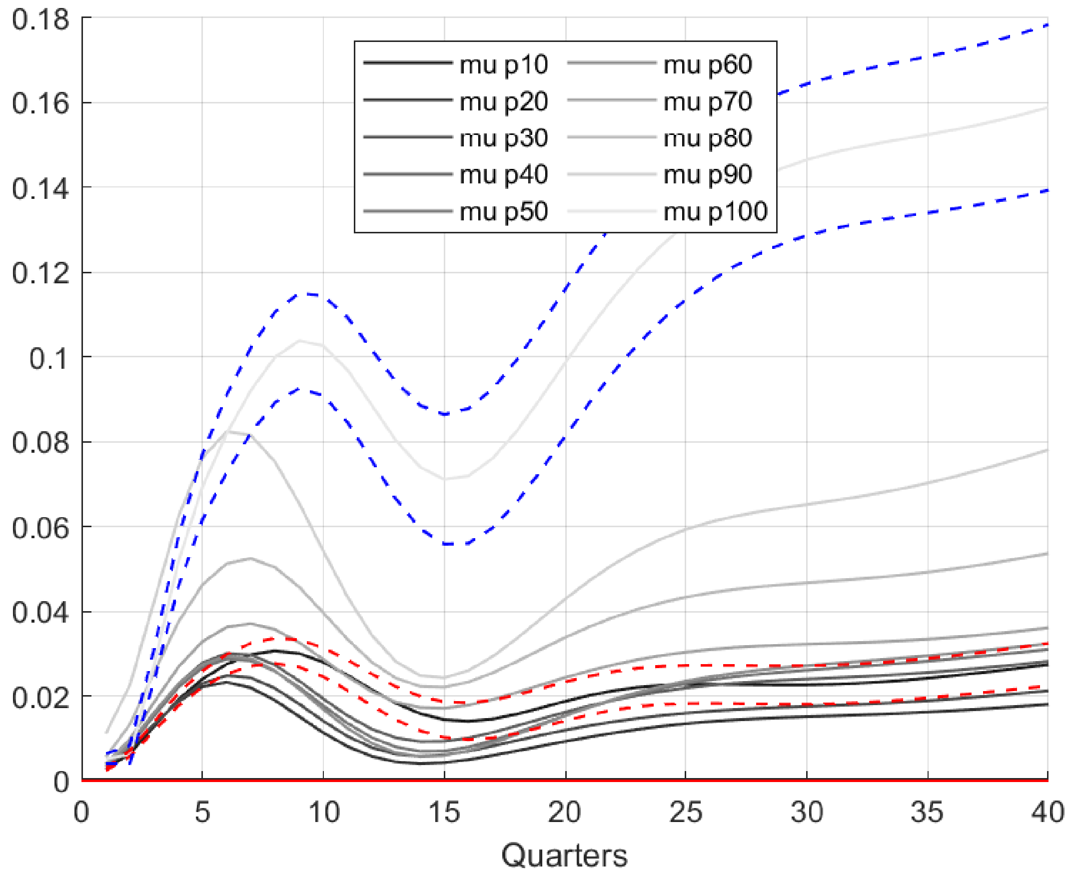


Figure 13: Impulse Response Function of the distribution of firms markups to a shock of M&A Deals. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

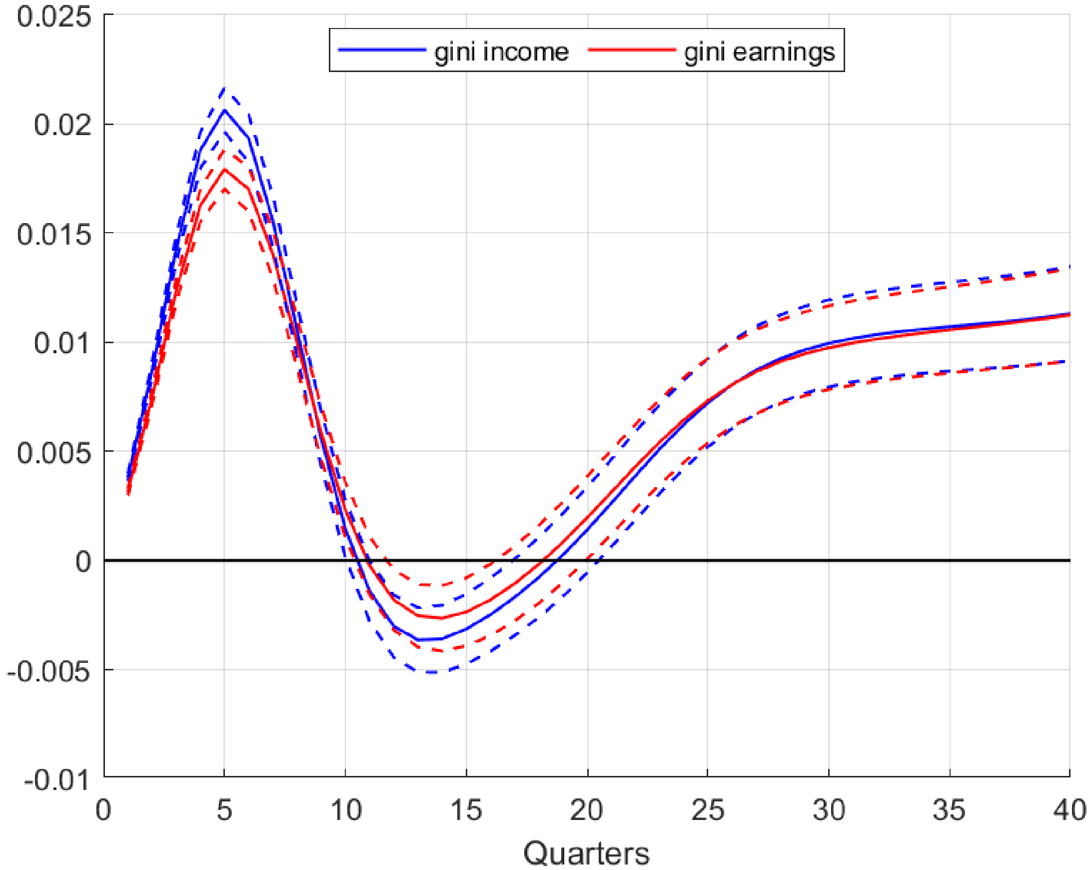


Figure 14: Impulse Response Function of Gini index for Income and Earnings to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

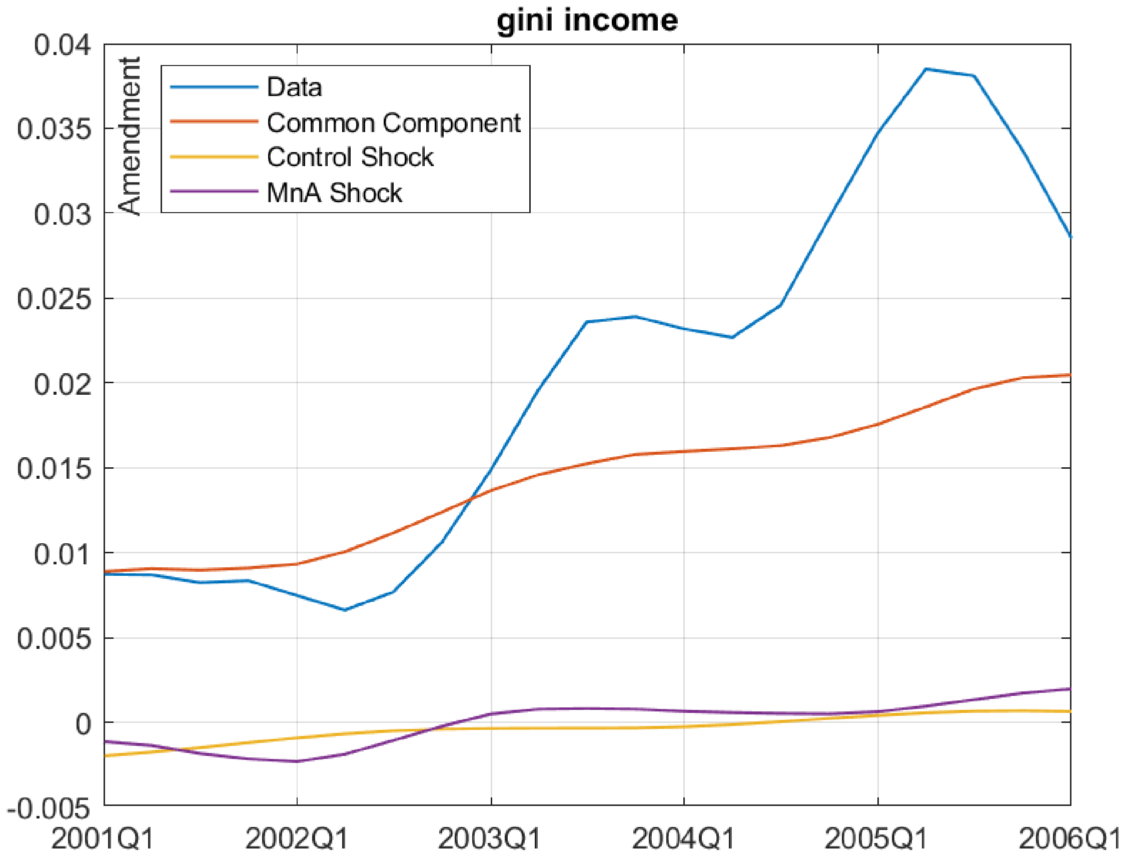


Figure 15: Historical Decomposition of Gini Index for household income. The variable is centered, so that the level of the vertical axes is not relevant. The scale is preserved, though, meaning that Gini Index increased by roughly 2 Gini points from 199Q1 to 2006Q4. Common Component represents the portion of the variable which is explained by the model, while M&A Shock represent the portion of the variable which is explained by the identified shock.

M&A Deal Value in place of number of M&A Deals

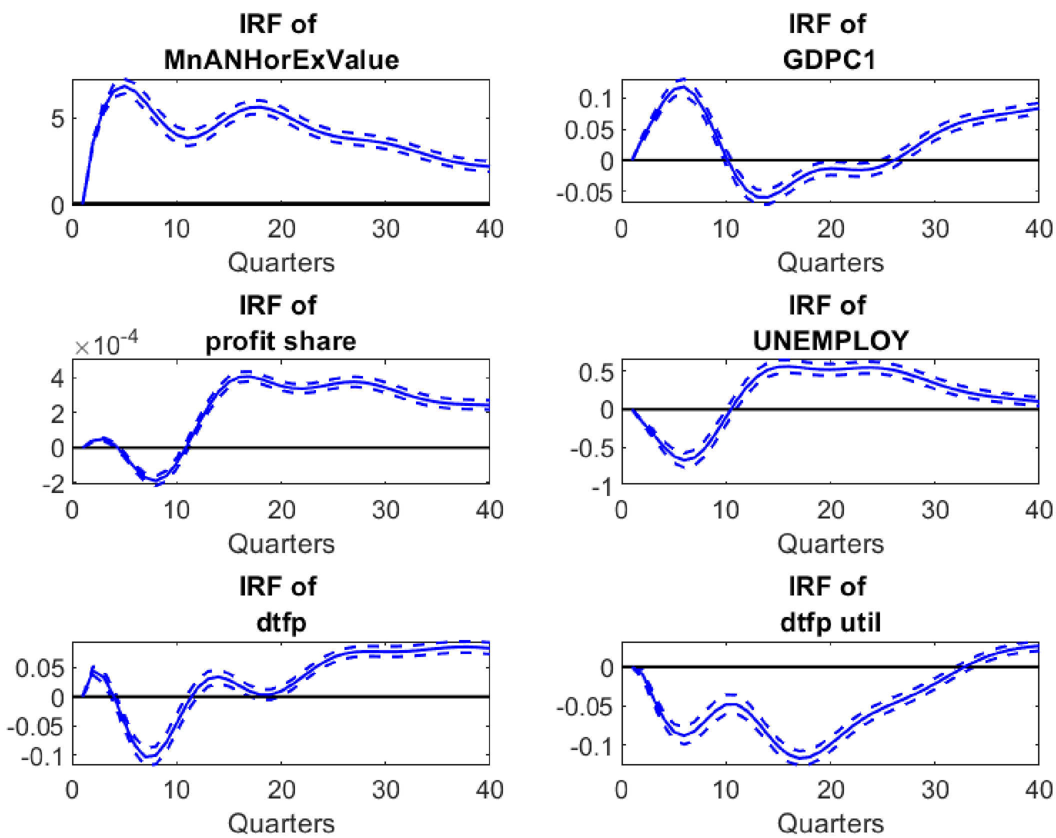


Figure 16: Impulse Response Function of macro variables to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

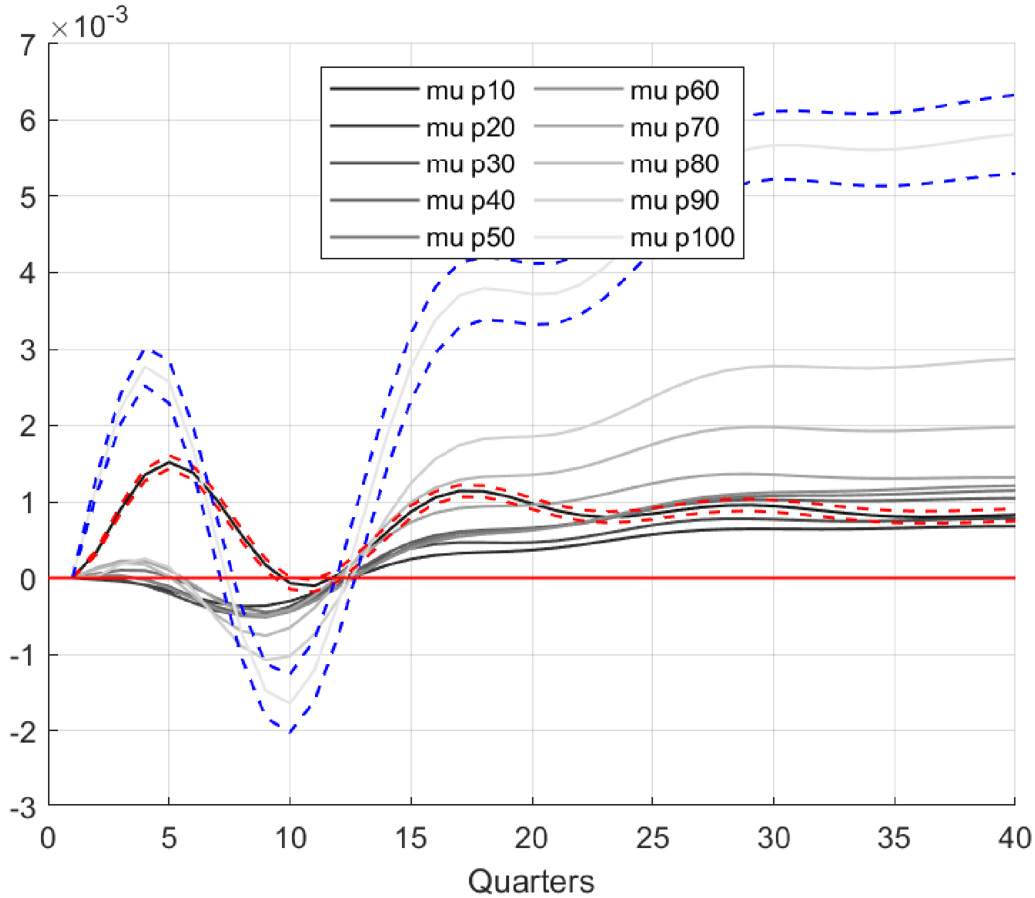


Figure 17: Impulse Response Function of the distribution of firms markups to a shock of M&A Deals. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

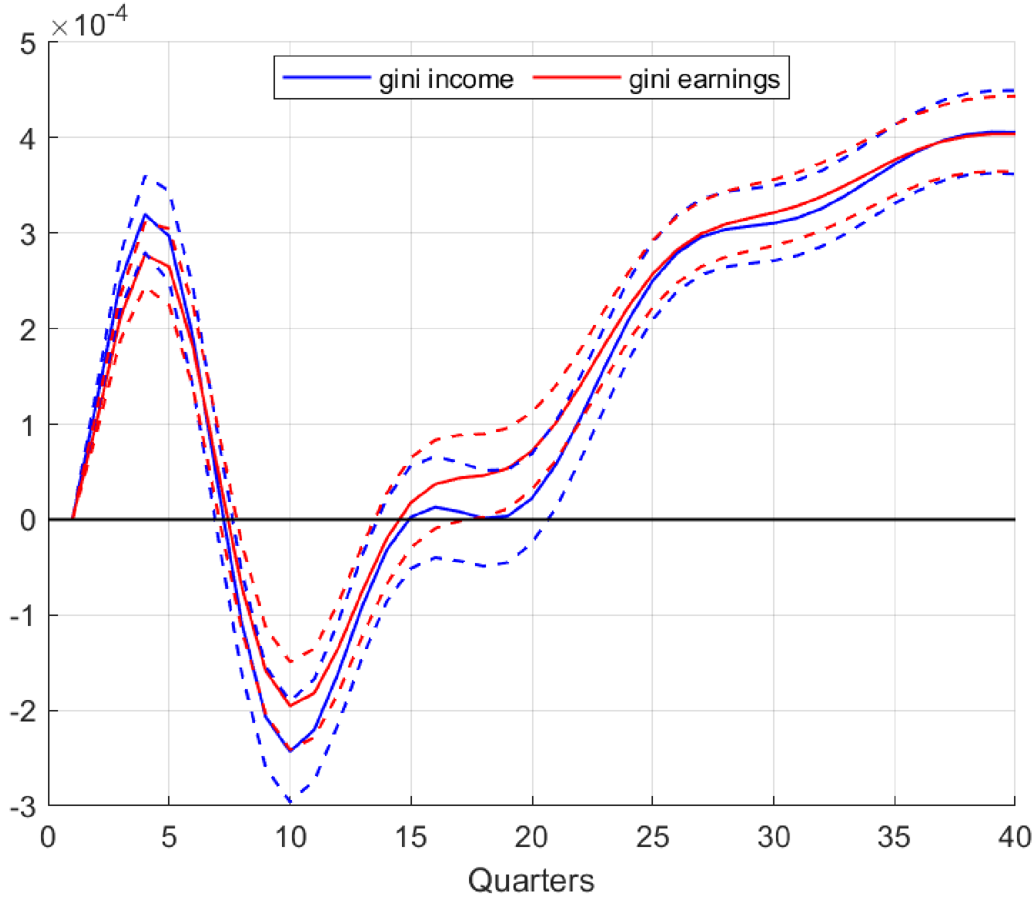


Figure 18: Impulse Response Function of Gini index for Income and Earnings to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

Markups without fixed costs

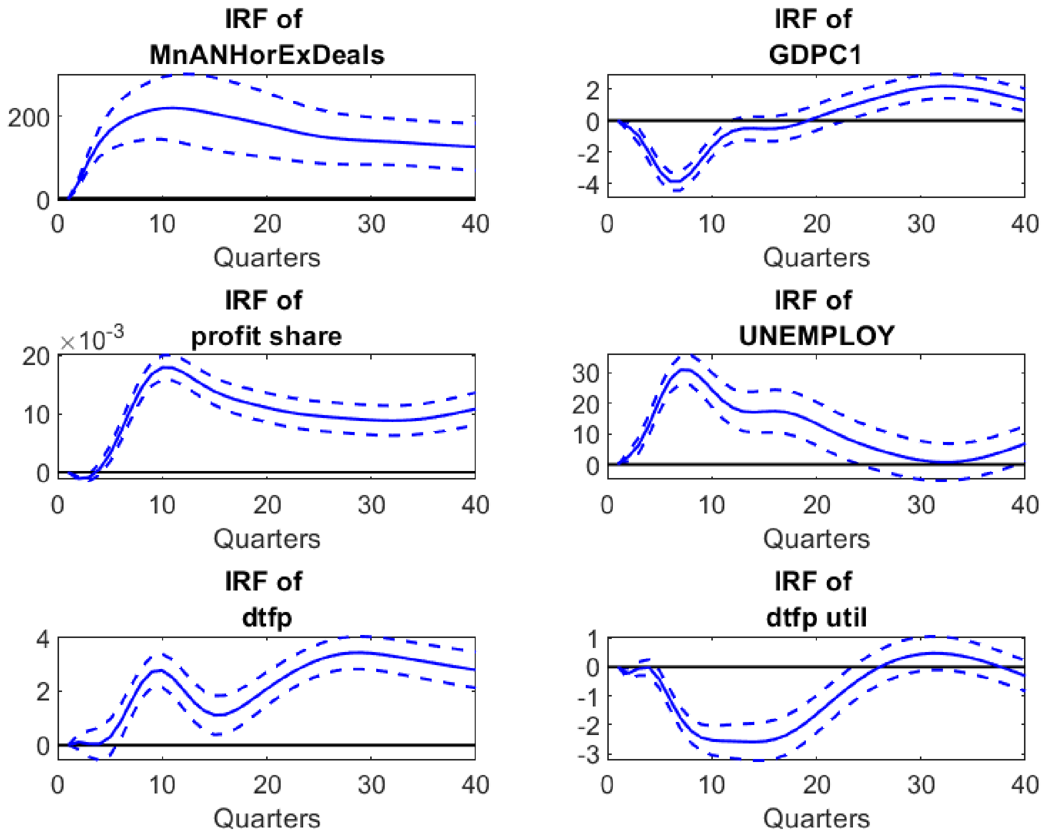


Figure 19: Impulse Response Function of macro variables to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

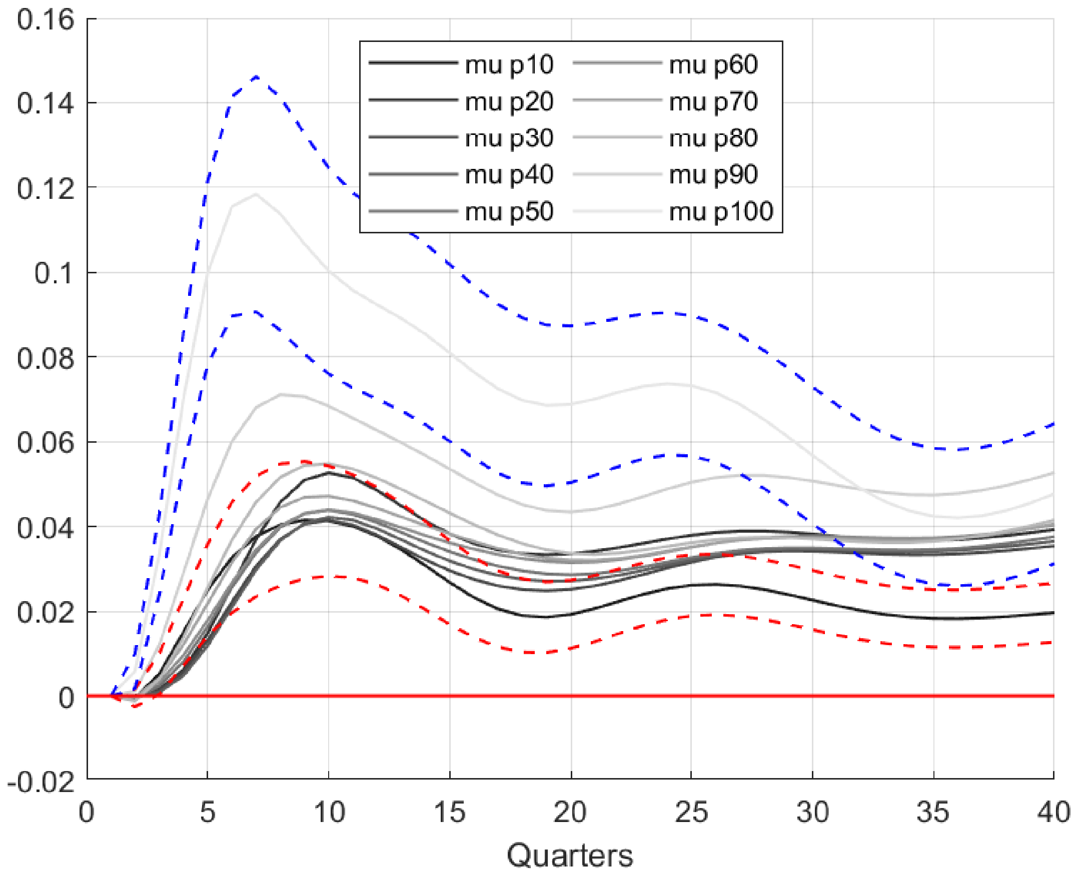


Figure 20: Impulse Response Function of the distribution of firms markups to a shock of M&A Deals. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

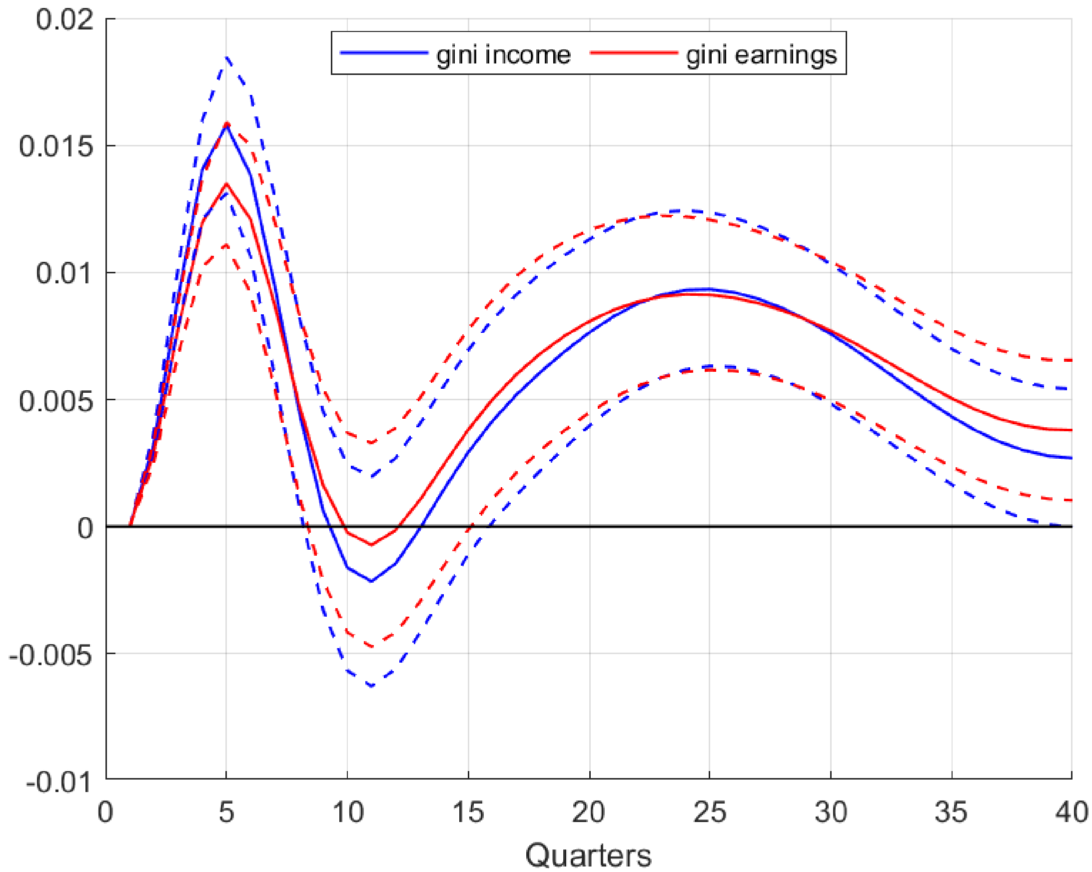


Figure 21: Impulse Response Function of Gini index for Income and Earnings to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

All M&A Deals

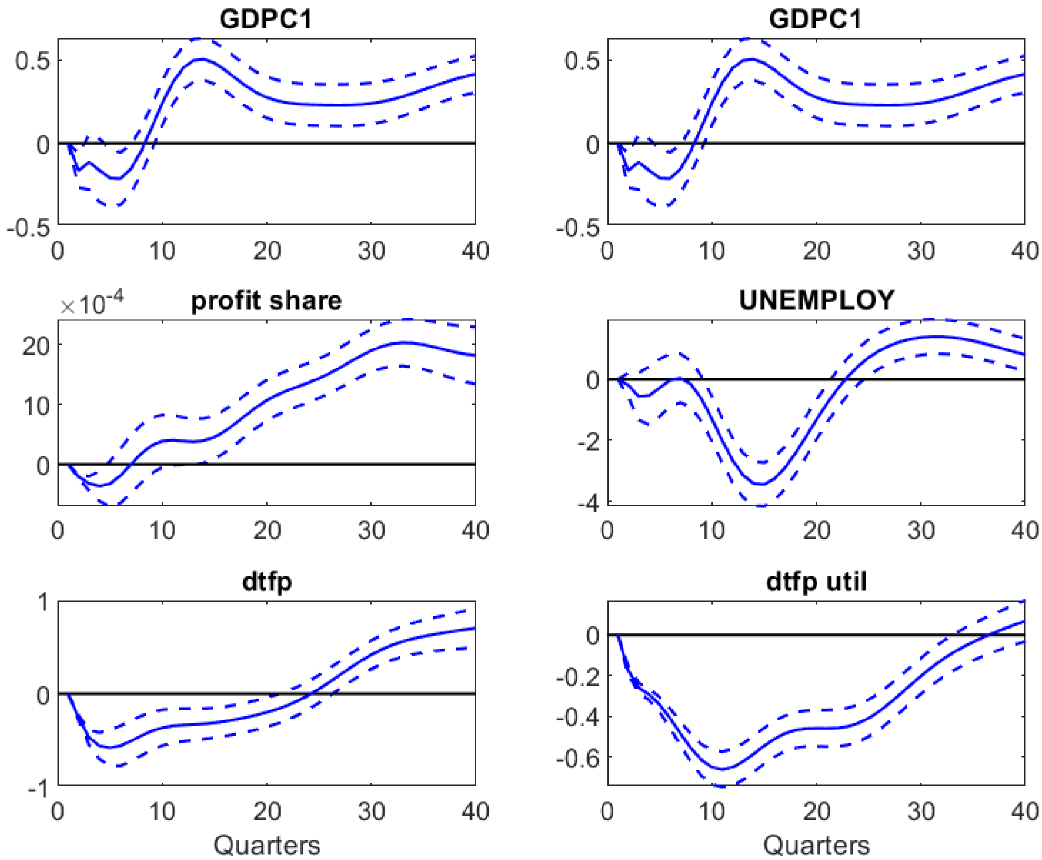


Figure 22: Impulse Response Function of macro variables to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

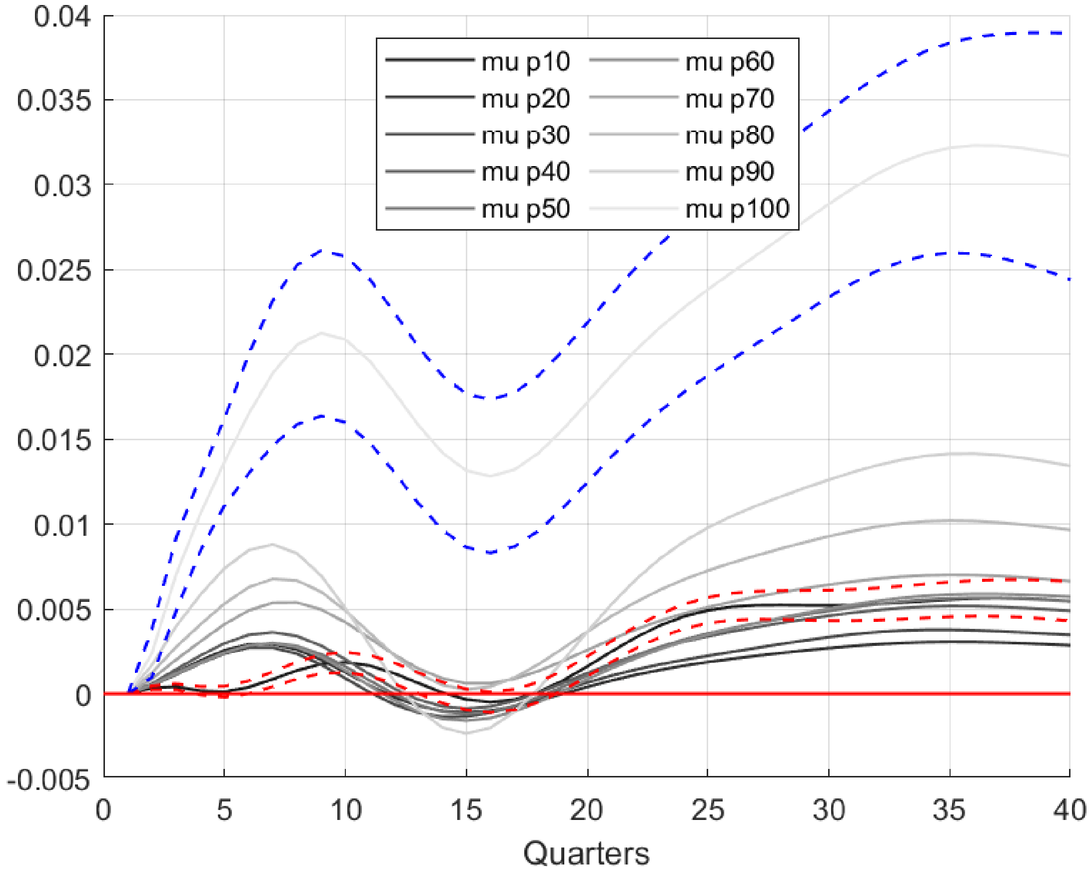


Figure 23: Impulse Response Function of the distribution of firms markups to a shock of M&A Deals. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

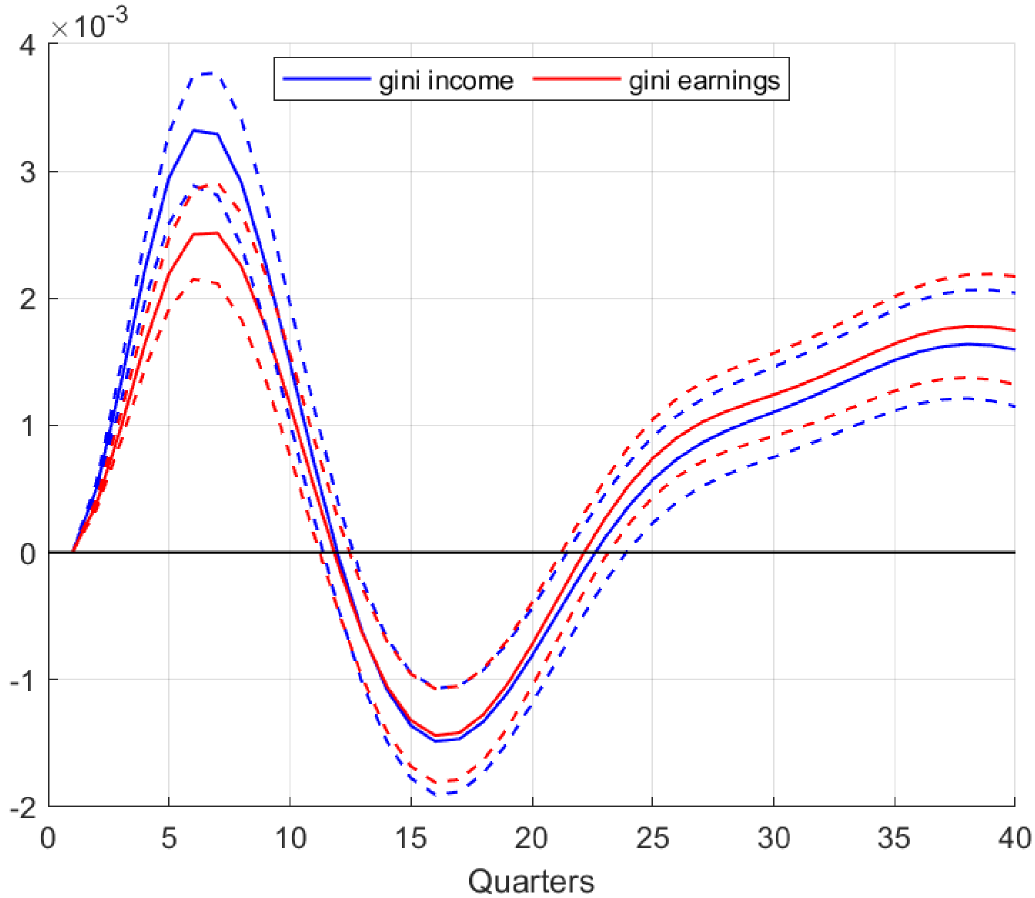


Figure 24: Impulse Response Function of Gini index for Income and Earnings to a shock of M&A Deals. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation of the distribution of bootstrapped IRFs.

Sign Restrictions

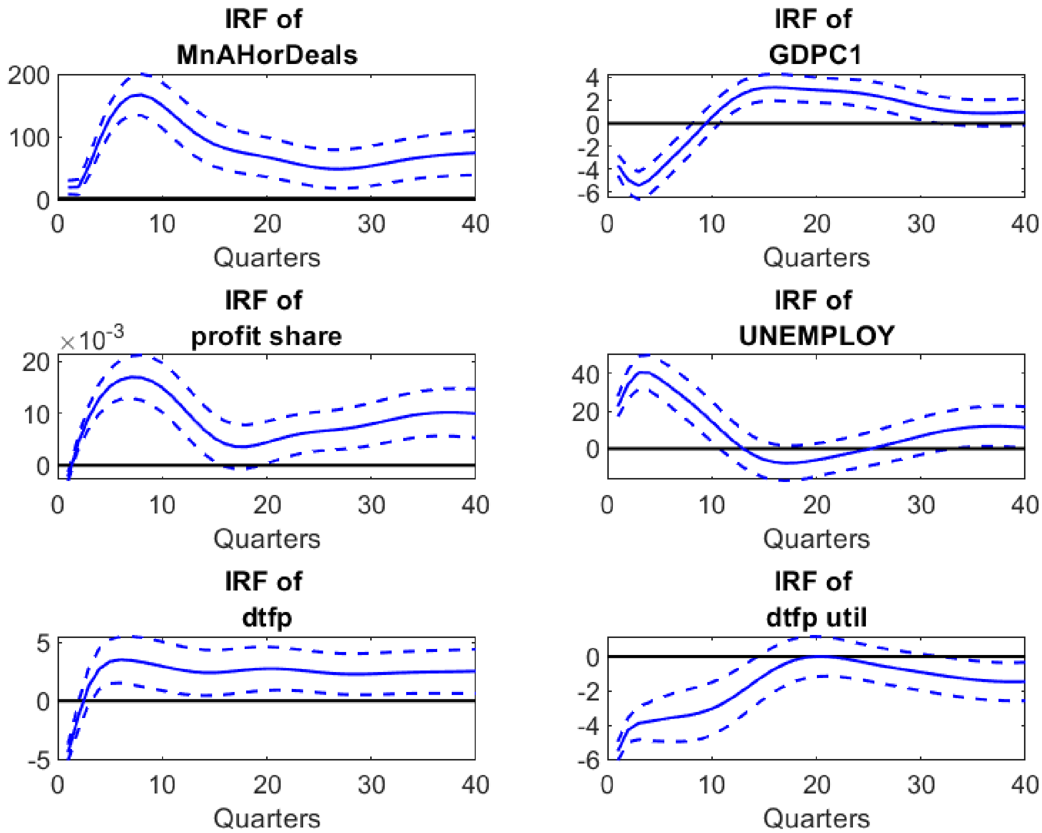


Figure 25: Impulse Response Function of macro variables to a shock identified using Sign Restrictions. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.

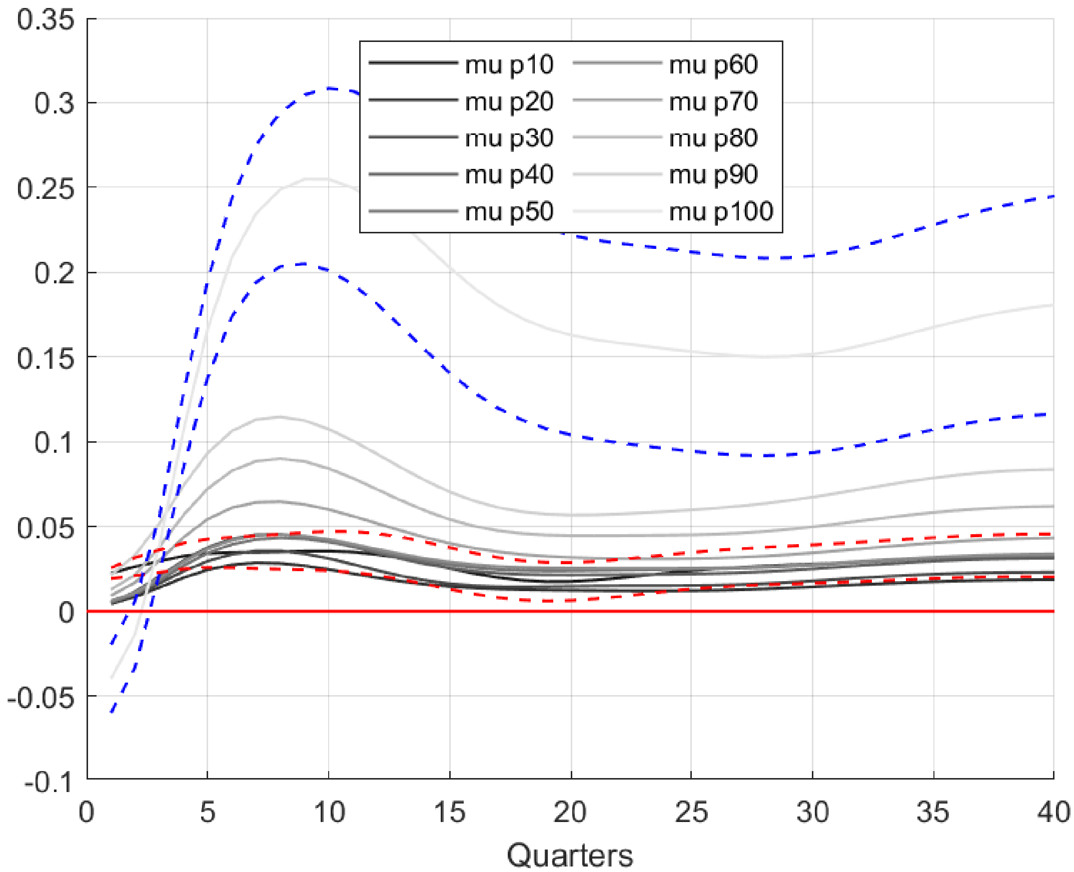
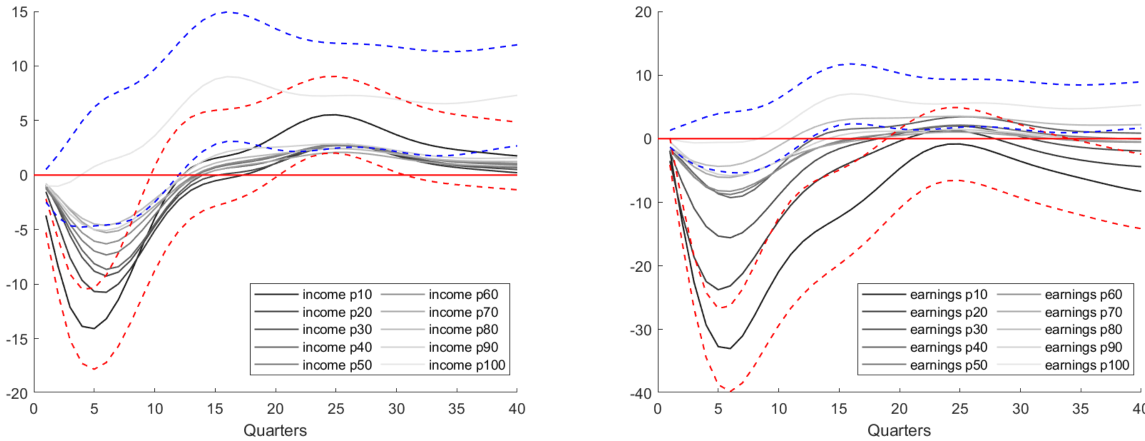
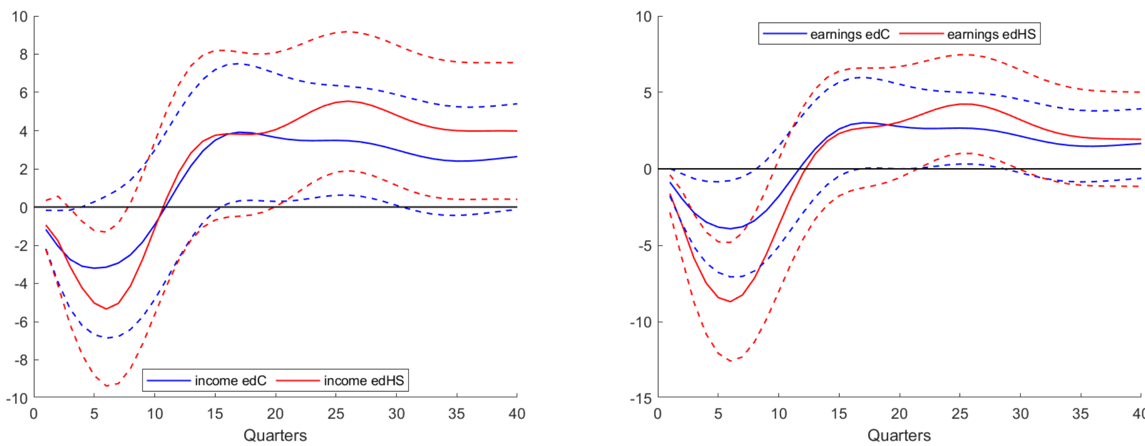


Figure 26: Impulse Response Function of the distribution of firms markups to a shock identified using Sign Restrictions. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.



(a) Income Deciles

(b) Labor Earnings Deciles



(c) Income by Education

(d) Earnings by Education

Figure 27: Impulse Response Function of the distribution of Hoouseholds variables to a shock identified using Sign Restrictions. Confidence bands for the 10th decile are reported in blue and for the 1st decile are reported in red. Confidence bands are computed by bootstrap methods on the process generating factors. Bands represent one standard deviation (or 68%) of the distribution of bootstrapped IRFs.

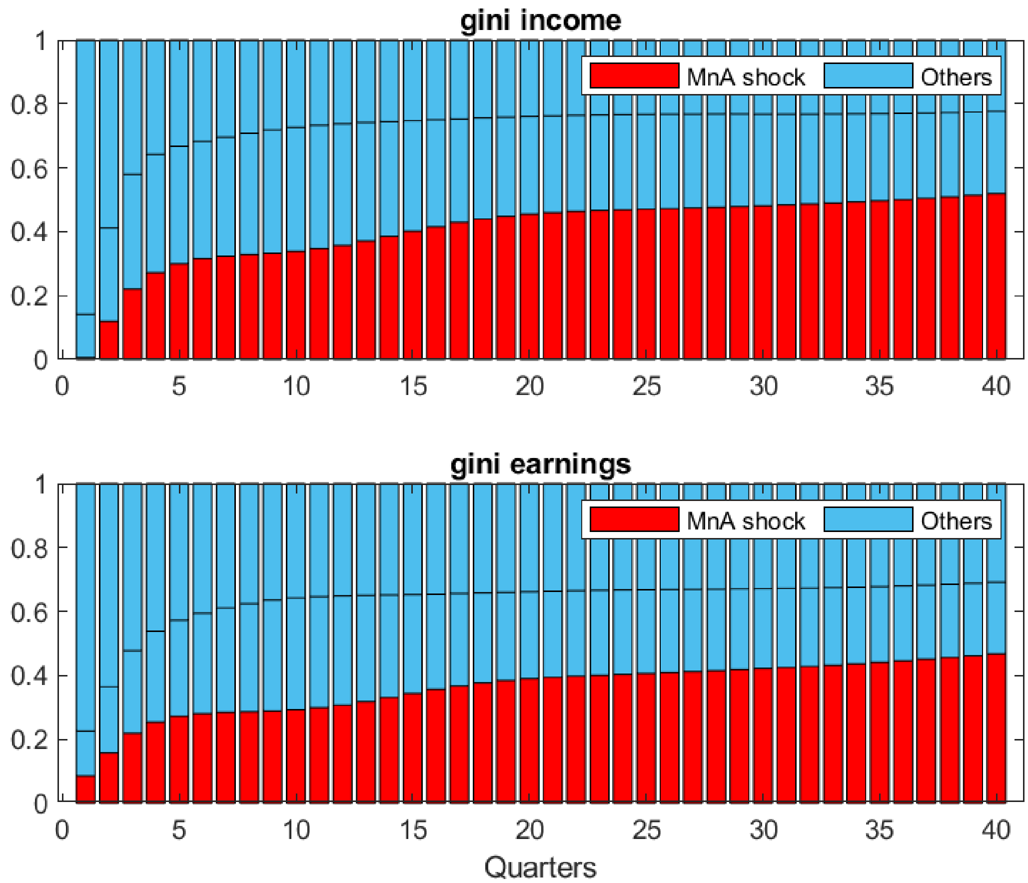


Figure 28: Error Variance Decomposition of the common component of several variables. The shock of interest is the one on which sign restrictions are imposed, and it is reported in red.