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Heterogeneity in Manufacturing Growth Risk

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Abstract

We analyze differences in output growth risk with respect to financial conditions across U.S. manufacturing industries. Using a multi-level quantile regression approach, we find strong heterogeneity in growth risk, particularly between the more vulnerable durable goods sector and the more resilient nondurable goods sector. Moreover, we show that industry characteristics significantly explain these differences. Large, or material intensive durable goods producing, or energy intensive nondurable goods producing industries are more vulnerable to adverse financial conditions, while industries engaging in labor hoarding, or with a high capital or overhead labor intensity are less susceptible.

Keywords: Downside risk, business cycle, quantile regression, manufacturing, financial conditions

JEL Classification: C21, E32, E44, L16, L60

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1 Introduction

In light of the Great Recession, quantifying and monitoring the evolution of risks in economic activity has become an essential task of policy makers and private sector participants. For example, investors need to understand and oversee macroeconomic risks in order to build well-diversified portfolios (Amenc et al., 2019), while central bankers and other policy makers strive for economic and financial stability by putting additional emphasis on minimizing risks rather than only focusing on optimizing expected outcomes (Kilian and Manganelli, 2008; Sánchez and Röhn, 2016; Prasad et al., 2019).[1] There exists clear evidence that the risk of an economic downturn is theoretically and empirically associated with deteriorating financial conditions (Bernanke et al., 1999; Gilchrist and Zakrajšek, 2012; Arellano et al., 2018). In particular, downside risks to the economy increase in the presence of tightening financial conditions, while upside potential seems to remain stable (Giglio et al., 2016; Adrian et al., 2019). Consequently, analyzing the relationship between downside macroeconomic risks and financial conditions has become a focal point of research (see, for example, Delle Monache et al., 2020; Plagborg-Møller et al., 2020; Falconio and Manganelli, 2020).

Most empirical work on downside macroeconomic risks and their relationship with financial conditions addresses the aggregate (often countrywide) level. However, we argue that analyzing disaggregate data is useful too and can provide additional insights. There is indeed strong empirical evidence that aggregate economic fluctuations can originate from industry-specific shocks (Foerster et al., 2011; Acemoglu et al., 2012; Carvalho and Gabaix, 2013). At the same time, Bloom (2014) shows that an economic downturn substantially increases the cross-sectional dispersion in growth rates across industries. To understand this increased heterogeneity at the advent of and during a recession, we believe that more attention should be given to the issue how downside macroeconomic risks, stemming from tight financial conditions, differ across industries and how these differences can be explained. This is what we will do in this paper.

To adress this issue, we use a multi-level quantile regression approach to analyze

[1]For direct evidence, see the statement in the August 2020 speech of Jerome H. Powell, chair of the Board of Governors of the Federal Reserve System: "Our policy actions continue to depend on the economic outlook as well as the risks to the outlook, including potential risks to the financial system that could impede the attainment of our goals." (https://www.federalreserve.gov/newsevents/speech/powell20200827a.htm)

and explain the variation in growth risk across U.S. manufacturing industries and their relationship with financial market conditions. More specifically, following Adrian et al. (2019), we first use quantile regressions to quantify industry-level output growth risk as a function of current financial and economic conditions, which flexibly allows for possibly asymmetric effects on industry growth. Next, inspired by Petersen and Strongin (1996), we analyze the heterogeneity in these growth vulnerabilities by linking them to industry characteristics that could signal why some industries are more at risk than others.

We consider monthly industrial production (IP) growth of 74 U.S. manufacturing industries at the four-digit level of the North American Industry Classification System (NAICS) over the period January 1973 to July 2020. We use the National Financial Conditions Index (NFCI) of the Federal Reserve Bank of Chicago to gauge U.S. financial conditions. Our main findings are twofold. First, we document significant heterogeneity across industries in how strongly their output growth risk is affected by the NFCI, based on the slope homogeneity tests of Galvao et al. (2018). For the large majority of industries, we find a pronounced nonlinear relationship between output growth and the NFCI. In particular, deteriorating financial conditions have a much stronger negative effect on downside risks than on central parts of the growth distribution, while upside potential is almost not affected at all. This is in line with the relationship found between the NFCI and aggregate output growth, see Adrian et al. (2019), among others. On average, a one standard deviation positive shock in the NFCI leads to a decline in the median and five percent quantile of three-month ahead IP growth of 0.237% and 0.773%, respectively, and an increase in the 95 percent quantile growth of 0.042%. However, some industries, in particular computer, aerospace and food, seem to be completely unaffected by the NFCI across all parts of the growth distribution.

Second, we show that the growth vulnerability differences can be significantly and meaningfully explained by industry characteristics. Most prominently, the durable goods sector is more vulnerable to adverse financial conditions than the nondurable goods sector. The average impact of the NFCI on the five percent quantile of three-month ahead IP growth is in fact twice as strong for durable goods producing industries as for nondurables. This concurs with Petersen and Strongin (1996), who show that the durable goods sector is three times more cyclical than the nondurable goods sector. Based on all manufacturing industries, we additionally find that large industries have more vulnerable growth, whereas industries that are capital intensive, overhead labor intensive, or engaging in labor hoarding have less susceptible growth. That the industry size and amount of capital are determinants of industry cycles is also found by Braun and Larrain (2005), while the characteristics considered by Petersen and Strongin (1996) are not found to be significant for the total manufacturing sector, except for durability. When we zoom in and compare the durable with the nondurable goods sector, we observe different characteristic effects. In particular, within the durable goods sector, the industry size, materials intensity and overhead labor intensity significantly explain part of the variation in the effects of the NFCI on downside production growth. These latter two effects agree with Petersen and Strongin (1996), where the materials intensity is in fact found to be the most important feature in signalling cyclical sensitivity. Yet, we deviate from their results as we do not find energy intensity, production labor intensity and concentration ratio to be significant. Within the nondurable goods sector, on the other hand, we find that the energy intensity and labor hoarding measure explain part of the downside risk variation, where the latter is the only significant effect found for nondurables in Petersen and Strongin (1996).

These findings have implications for policy makers who strive for economic stability in the manufacturing sector. For example, in order to minimize downside growth risks with respect to financial conditions, it might be more effective to opt for industry-level policy rather than nationwide policy as there is large industry heterogeneity (OECD, 2003, Ch. 3).[2] These policies can in turn be based on the industry characteristics that signal which industries are more at risk. Alternatively, investors could exploit the heterogeneity across industries in their construction of industry-rotation strategies that are less vulnerable to adverse shocks in the financial market.

Our work is closely related to and builds on two strands of literature. First, it relates to the existing literature on industry heterogeneity in output growth. For example, Berman and Pfleeger (1997) show that some industries are more sensitive to the business cycle than others, particularly industries in the durable goods sector are far more cyclical than industries in the nondurable goods sector (Mitchell, 1951; Lucas, 1977; Bernanke, 1983; Petersen and Strongin, 1996). We add to this literature by showing that some industries

[2]For practical motivation, see also McKinsey's "How to compete and grow: A sector guide to policy" (`https://www.mckinsey.com/industries/public-and-social-sector/our-insights/how-to-compete-and-grow`)

are more affected by shocks in the financial market than others, where this is strongest for durable goods producing industries. Within the durable goods sector, Petersen and Strongin (1996) show that industries with a larger share of variable costs relative to fixed costs are more cyclical, whereas industries engaging in labor hoarding, that is, the retaining of employees due to sunk costs of searching, hiring and training (Becker, 1962; Oi, 1962; Rosen, 1968), are less cyclical. Specifically, nonproduction workers require, on average, more firm-specific investments than production workers (Parsons, 1986) and are thus more subject to labor hoarding (Rotemberg and Summers, 1990). As a result, overhead labor intensive industries are also less cyclical (Petersen and Strongin, 1996). Indeed, we find that industries that are overhead labor intensive or engaging in labor hoarding have less vulnerable growth. Another important driver of cyclical fluctuations is an industry's market structure such as its concentration ratio (Domowitz et al., 1985, 1988), although we are not able to confirm this result for downside growth risk. Lastly, Korenok et al. (2009) and Chang and Hwang (2015) show that there are large differences across industries in the duration of recessions and expansions as well as how strong this asymmetry is within an industry, while there is also heterogeneity in the leads and lags of industry cycles (Fok et al., 2005; Camacho and Leiva-Leon, 2019) and the effects of monetary policy on industry-level output (Dedola and Lippi, 2005). Our findings confirm that there is clear industry heterogeneity in the asymmetry of the growth distribution, particularly in the presence of tight financial conditions.

Second, our work is related to the more recent and rapidly expanding literature on downside macroeconomic risks (also known as growth-at-risk) and their relationship with current market conditions. A substantial part of this literature employs quantile regressions to quantify downside macroeconomic risks as a function of financial and economic conditions (Giglio et al., 2016; Adrian et al., 2018, 2019; Loria et al., 2019; Adams et al., 2021; De Santis and Van der Veken, 2020; Figueres and Jarociński, 2020; Reichlin et al., 2020). In turn, the quantile regression approach to measuring these macroeconomic risks has been extended to a multivariate setting by means of quantile vector autoregressions (Chavleishvili and Manganelli, 2019; Falconio and Manganelli, 2020; Chavleishvili and Kremer, 2021) or to data-rich environments by including a large number of predictors with variable selection or dimension-reduction techniques (Cook and Doh, 2019; Plagborg-Møller et al., 2020; Chen et al., 2021). Alternatively, Adrian et al. (2021)

consider a nonparametric approach to examine the joint distribution of economic and financial conditions, whereas Brownlees and Souza (2020), Carriero et al. (2020a,b) and Delle Monache et al. (2020) follow a fully parametric approach to forecast downside risks. Nonetheless, the avenue of looking at disaggregate data in the context of growth-at-risk has, to the best of our knowledge, not been pursued yet.

We contribute to both strands of literature. First and foremost, we provide new insights in the macroeconomic risk literature by focusing on industry-level output growth risk instead of only aggregate growth risk. By doing so, we allow for heterogeneity across industries in their growth vulnerability and to what extent their downside risk is related to current financial and economic conditions. Notably, we document substantial industry variation in downside growth risk, which enriches the key findings of Adrian et al. (2019) for aggregate output and emphasizes the notion to also look at more disaggregated levels in the economy. Second, we extend the work of Petersen and Strongin (1996), who analyze in a linear setting why some industries are more cyclical than others. Instead, we allow for a more flexible and possibly nonlinear relationship between output growth and current market conditions by means of quantile regressions, after which we examine which industry characteristics explain why some industries are more vulnerable to adverse financial conditions for specific parts of the growth distribution. Empirically, we find similar industry-characteristic effects as Petersen and Strongin (1996) for downside risks, which could be attributed to the fact that business and financial cycles are closely intertwined (Claessens et al., 2012).

Our paper is organized as follows. Section 2 introduces our multi-level quantile regression approach. Section 3 discusses the NFCI and U.S. manufacturing industry data. Section 4 presents the industry-level results and shows how to explain the heterogeneity in growth vulnerability across industries. Section 5 summarizes our main conclusions.

2 Multi-level quantile regression approach

Following Adrian et al. (2019), we first employ quantile regressions (Koenker and Bassett, 1978) to study the conditional distribution of industry-level output growth as a function of economic and financial conditions. Next, the set-up of Adrian et al. (2019) is extended with a second level, linking the quantile regression coefficients to industry characteristics.

By doing so, we can investigate whether these characteristics explain the differences in the effects of financial conditions across industries. Crucially, we account for estimation uncertainty from the first level in the inference of the second level by applying a bootstrap approach that we discuss later in this section. We refer to these two levels as the multi-level quantile regression approach, despite the fact that we estimate them sequentially in two steps rather than simultaneously.[3]

Let $y_{i,t}$ denote the monthly output growth of industry i in month t, $\bar{y}_{i,t+h} = \frac{1}{h}\sum_{j=1}^{h} y_{i,t+j}$ the average output growth of industry i between months t and $t+h$, and $NFCI_t$ the national financial condition index (NFCI) in month t. Then, following Adrian et al. (2019), we express the τth quantile of $\bar{y}_{i,t+h}$ conditional on $\boldsymbol{x}_{i,t} = \big(1, NFCI_t, y_{i,t}\big)'$ as

$$Q_{\bar{y}_{i,t+h}|\boldsymbol{x}_{i,t}}(\tau \mid \boldsymbol{x}_{i,t}) = \alpha_i(\tau) + \beta_i(\tau) NFCI_t + \phi_i(\tau) y_{i,t}, \tag{1}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T - h$, where N is the number of industries and T the number of months. For notational simplicity, we suppress the dependence of the quantile regression coefficients on the horizon h.

The coefficients $\beta_i(\tau)$ and $\phi_i(\tau)$ in equation (1) measure the effect of current financial and industry-level output conditions, respectively, on the τth quantile of average output growth of industry i over the next h months. In other words, they measure how vulnerable the growth of a specific industry is to the current market conditions. We implement the quantile regressions in equation (1) for different values of τ covering the complete range between 0.05 and 0.95. However, given the focus of policy makers and investors on downside risks in output growth, we are particularly interested in these effects for smaller values of τ.

We also consider two alternative quantile regression models. First, we extend the specification in equation (1) by including additional lags of $y_{i,t}$ as well as other macro-financial control variables. Specifically, we follow Gilchrist and Zakrajšek (2012) and consider the term spread, real federal fund rate, credit spread and excess bond premium. This extended quantile regression leads to qualitatively similar results for the relationship between industry output growth and financial conditions, see Appendix A for complete details. Second, we consider the heterogeneous panel quantile regression model with

[3] Alternatively, one could estimate the multi-level quantile regression model in a one-step approach by putting it in a Bayesian estimation framework, see for example Chang (2015).

interactive fixed effects of Ando and Bai (2020), where the unobserved heterogeneity is modelled with a latent factor structure. Similarly, this model generates qualitatively comparable results as the industry-specific quantile regressions in equation (1), see Appendix B for further details.

For each industry i and a given quantile τ, we estimate the quantile regression coefficients as

$$\hat{\boldsymbol{\theta}}_i(\tau) = \underset{\boldsymbol{\theta}_i(\tau)}{\arg\min} \frac{1}{T} \sum_{t=1}^{T-h} \rho_\tau \Big(\bar{y}_{i,t+h} - \boldsymbol{x}'_{i,t} \boldsymbol{\theta}_i(\tau) \Big), \quad i = 1, \ldots, N, \tag{2}$$

where $\boldsymbol{\theta}_i(\tau) = \big(\alpha_i(\tau), \beta_i(\tau), \phi_i(\tau)\big)'$ and $\rho_\tau(u) = u\big(\tau - \mathbb{I}\{u \leq 0\}\big)$ is the standard check function of quantile regressions (Koenker and Bassett, 1978).[4] As advocated by Buchinsky (1995), we consider a bootstrap approach to determine the confidence bounds of the quantile regression estimators $\hat{\boldsymbol{\theta}}_i(\tau)$. More specifically, we apply the stationary bootstrap of Politis and Romano (1994) to jointly re-sample the industry-level output and NFCI, while preserving the autocorrelation and interdependence structure of the series. The expected block size is determined using the method of Politis and White (2004) with the correction of Patton et al. (2009), where we take the maximum expected block size of the industry output and NFCI series for the jointly re-sampling approach.[5] We consider 1,000 bootstrapped samples to compute the confidence bands.

In the second level of the model we implement the cross-sectional regression of the form

$$\beta_i(\tau) = \boldsymbol{\delta}(\tau)'\boldsymbol{w}_i + \eta_i, \quad i = 1, \ldots, N, \tag{3}$$

for a specific quantile τ, where $\boldsymbol{w}_i$ is a $(K+1) \times 1$ vector containing a constant and K time-invariant industry characteristics of industry i. The industry characteristics are standardized with mean zero and variance one for interpretation purposes. For each industry i and quantile τ, the coefficients $\delta_k(\tau)$ for $k = 2, \ldots, K+1$ measure the effect of the kth industry characteristic on the quantile regression coefficient corresponding to

[4] We minimize the objective function using the interior point (Frisch-Newton) algorithm via the Matlab package available on Roger Koenker's website: http://www.econ.uiuc.edu/~roger/research/rq/rq.html

[5] For all industries (except for beverages and motor vehicles), this leads to an expected block size equal to 36.76 that corresponds to the NFCI series. Unreported results show that taking the mean instead of the maximum generates qualitatively similar results.

the NFCI. Hence, they indicate how strongly an industry characteristic attributes to the output growth vulnerability of a specific industry with respect to financial market conditions.

We estimate this second level by plugging in the estimated coefficients $\hat{\beta}_i(\tau)$ of the first-level quantile regressions and conducting ordinary least squares (OLS) estimation. Importantly, we construct confidence bands of the estimator $\hat{\boldsymbol{\delta}}(\tau)$ that account for the estimation uncertainty related to the first-level quantile regression coefficients. This is achieved by a bootstrap approach where, for each bootstrapped estimator $\hat{\beta}_i^b(\tau)$ for $b = 1, \ldots, 1,000$, we conduct the linear regression in equation (3) to obtain the bootstrapped estimator $\hat{\boldsymbol{\delta}}^b(\tau)$ for $b = 1, \ldots, 1000$. These can then be used for valid inference in the second level, while accounting for the estimation uncertainty of the first level.

3 Data

We consider monthly growth rates of industrial production (IP) indices for 74 U.S. manufacturing industries over the period January 1973 to July 2020. The data is obtained from the Federal Reserve.[6] We select the industries that are available at the four-digit level of the 2012 North American Industry Classification System (NAICS).[7] In case the four-digit NAICS level is not available, we take the three-digit NAICS level instead. The final selection of U.S. manufacturing industries is the same as used by Chang and Hwang (2015), see Appendix D for a complete overview.

To measure financial conditions, we use the National Financial Conditions Index (NFCI) of the Federal Reserve Bank of Chicago. The NFCI is a weekly gauge of the conditions in U.S. money, debt and equity markets, and the traditional and shadow banking systems.[8] A positive NFCI value indicates tighter-than-average financial conditions, whereas negative values indicate looser-than-average financial conditions. The NFCI is constructed with a large dynamic factor model that is estimated with the quasi-

[6] See the G.17 industrial activity data section at https://www.federalreserve.gov/releases/g17/current/default.htm

[7] We also consider disaggregation at a lower (three-digit) and higher (six-digit) NAICS level. Overall, our results are robust to the choice of disaggregation level (see Appendix C), but we focus on the four-digit NAICS level to have a large enough cross-section, while keep having data available for all industry characteristics as the capital intensity is not available at the six-digit NAICS level.

[8] For more information on the NFCI and its decomposition, see https://www.chicagofed.org/publications/nfci/index

maximum likelihood approach of Doz et al. (2012) and can be obtained from the Federal Reserve Bank of St. Louis.[9] We refer to Brave and Butters (2011) for more details on the construction of the NFCI. The weekly observations are averaged to obtain monthly NFCI observations over the period January 1973 to July 2020, where the rule of the Federal Reserve Bank of St. Louis states that the weeks overlapping two months are assigned to the later month.

Figure 1 shows the time series of the average industrial production growth rate between months t and $t+3$ (that is, $\bar{y}_{i,t+3}$) and the NFCI in month t for a selection of four industries. For plastics, alumina and motor vehicle parts, we observe that positive values of the NFCI coincide with large negative industrial production growth, which is consistent with the findings of Adrian et al. (2019) for aggregate GDP growth. At the same time, it seems that the strength of this relationship varies across industries, with growth

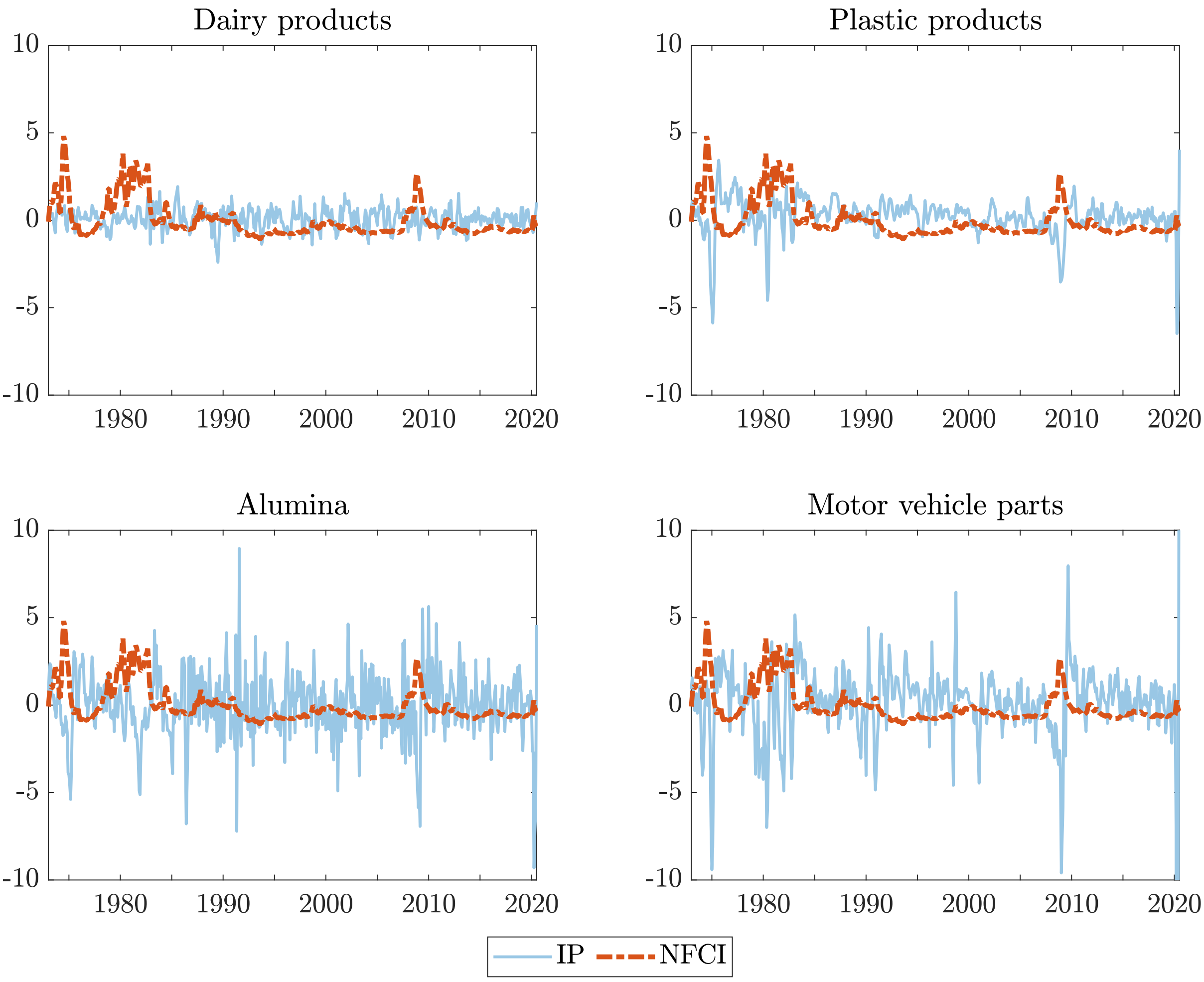

Figure 1: Time series of four industries' three-month average IP growth and the NFCI

[9]The NFCI data is obtained from https://fred.stlouisfed.org/series/NFCI

in motor vehicle parts showing a much stronger response than alumina and especially plastics. In fact, for dairy products this relationship seems to be nonexistent altogether. This already suggests the presence of heterogeneity across industries in their sensitivity to financial conditions.

To analyze why some industries might be more at risk, we select a set of industry characteristics that are considered to be informative about the variation in industry business cycles (Petersen and Strongin, 1996). These characteristics can be divided in four categories: (i) production input factors, that is, capital intensity, materials intensity, energy intensity and production labor intensity, (ii) labor hoarding, that is, overhead labor intensity and a correlation-based labor hoarding measure, (iii) market power and (iv) industry size.

The production input factors, labor hoarding measures and industry size can be constructed with data from the NBER-CES Manufacturing Industry Database (Bartelsman and Gray, 1996), which contains annual observations on output, employment, payroll and other inputs costs, investments, capital stocks, total factor productivity and various industry-specific price indices for the period 1958-2018.[10] The materials (excluding energy) intensity, energy intensity, and production and overhead labor intensities are computed as the total cost of the respective input divided by the value added of that industry. Moreover, we follow Petersen and Strongin (1996) by including a correlation-based labor hoarding measure that is computed as the negative correlation between the change in materials usage (measured as total cost of materials (including energy) deflated by an industry-specific materials deflator) and the change in production-worker hours. This implies that a correlation coefficient of one corresponds to no labor hoarding, which we multiply by minus one to make the direction of the effect consistent with a high overhead labor intensity. The size of an industry is measured as the percentage of value added with respect to total value added of the entire manufacturing sector. The capital intensity is constructed using annual data from the multi-factor productivity (MFP) tables of the U.S. Bureau of Labor Statistics (BLS) for the period 1987-2018 by dividing the total cost of capital by the total cost of labor.[11] Lastly, market power is measured as the four-firm concentration ratio, which measures the percentage of value added of the four

[10]The NBER-CES database is obtained from https://www.nber.org/research/data/nber-ces-manufacturing-industry-database

[11]The BLS-MFP data is obtained from https://www.bls.gov/mfp/

largest firms, and is taken from the Economic Census conducted every five-years by the U.S. Census Bureau, where we consider the years 2002, 2007 and 2012.[12]

Following Petersen and Strongin (1996) and Fok et al. (2005), we ignore time-variation in the industry characteristics and focus on the low-frequency aspects of the data by taking the average of the values over the available period of each characteristic. To evaluate the robustness of the industry-characteristic effects when they are based on different sample periods, we also conduct a subsample analysis of these effects later on in the results section.[13] Moreover, we follow the recommendation of Petersen and Strongin (1996) to also examine the durable and nondurable goods sectors separately to allow for different effects of these characteristics within each sector. We follow the classification of durable and nondurable goods sectors from the Federal Reserve, which results in 45 industries classified as durables and 29 industries as nondurables.[14]

Table 1 displays the summary statistics of the industry characteristics.[15] The means and standard deviations of the energy intensities, production and overhead labor intensities, and concentration ratios are roughly similar across durable and nondurable goods sectors, whereas the skewness measures display clear deviations. In contrast, the industry size, and capital and material intensities exhibit clear differences between the durable and nondurable goods sectors, particularly their means and standard deviations are substantially larger for nondurables (except for the standard deviation of value added). By looking at the skewness statistics, we see that most characteristics have a positively skewed distribution, with the strongest asymmetries for the energy and capital intensities in the durable and nondurable goods sectors, respectively. Lastly, the mean of the labor hoarding measure is -0.81 for the durables and -0.54 for nondurables, which indicates the presence of labor hoarding in both sectors. Still, the nondurable goods sector exhibits, on average, more labor hoarding as it is further away from absence of labor hoarding (that is, a value of minus one).

[12]The Economic Census data is obtained from https://www.census.gov/programs-surveys/economic-census.html. Note that the concentration ratios of the combined NAICS codes (e.g. Iron and steel products with code 3311,2) are based on the average four-firm ratios of its sub-industries.

[13]For additional insights in the time-variation of the industry characteristics and the robustness of our findings to specific starting dates, see Appendices E.1 and E.2, respectively.

[14]The classification is obtained from https://www.federalreserve.gov/releases/g17/SandDesc/sdtab1.pdf

[15]The cross-correlations of the industry characteristics are given in Appendix E.3. In short, multicollinearity is not an issue at the four-digit NAICS level.

Table 1: Summary statistics of U.S. manufacturing sector industry characteristics

	VA	**Cap.**	**Mat.**	**Energy**	**ProdL**	**OverL**	**LH**	**CR**
Panel A: Total manufacturing sector (74 industries)								
Mean	1.35	1.40	1.22	0.05	0.25	0.13	-0.71	0.31
Std.	1.01	1.95	0.74	0.05	0.08	0.05	0.22	0.17
Skew.	1.12	5.79	2.51	2.08	-0.32	0.71	1.57	0.93
Panel B: Durable goods sector (45 industries)								
Mean	1.24	0.82	1.06	0.05	0.27	0.15	-0.81	0.29
Std.	1.07	0.37	0.50	0.05	0.06	0.05	0.09	0.17
Skew.	1.47	1.18	1.36	2.39	0.09	0.75	1.03	0.84
Panel C: Nondurable goods sector (29 industries)								
Mean	1.52	2.31	1.46	0.05	0.21	0.11	-0.54	0.33
Std.	0.91	2.88	0.97	0.04	0.10	0.03	0.26	0.16
Skew.	0.48	3.76	2.11	1.31	0.23	-0.20	0.56	1.22

Notes: This table shows the summary statistics of annual (or quinquennial) average industry characteristics over their respective available period for the durable goods sector, nondurable goods sector or total manufacturing sector. We include the mean, standard deviation (std.) and skewness (skew.) of the following characteristics: Value added (VA), capital intensity (Cap.), materials intensity (Mat.), energy intensity (Energy), production labor intensity (ProdL), overhead labor intensity (OverL), labor hoarding (LH) and concentration ratio (CR).

4 Manufacturing growth risk

In this section we first analyze the results related to the industry-specific quantile regressions to assess how vulnerable manufacturing industries are with respect to financial conditions and how much heterogeneity there is among industries. Next, we examine which industry characteristics are able to explain this heterogeneity in growth risk.

4.1 Industry-specific growth risk

We start our analysis by presenting the estimated industry-specific NFCI quantile regression coefficients ($\hat{\beta}_i(\tau)$) from equation (1) for the industries in the durable and nondurable goods sectors in Figures 2 and 3, respectively. More specifically, we present the quantile regression coefficients for a small number of selected values of τ, that is, 5%, 50% and 95%, while results for the complete range of quantiles are discussed later. For comparison, we also display the OLS estimates of the corresponding linear regression coefficients. In general, we focus on three-month ahead IP growth (that is, $h = 3$), while the results for longer horizons (that is, $h = 6$ and 12) are given in Appendix F. In short, we generally find similar results for $h = 6$ and 12 as for $h = 3$, although the effects become less pronounced as the horizon increases.

Figures 2 and 3 show that, for both the industries in the durable and nondurable goods sectors, the NFCI has a much stronger negative effect on the 5% quantile of three-month ahead IP growth than on the central part of the growth distribution (as represented here by the mean and median). Indeed, Table 2 indicates that the average 5% quantile regression coefficient across all industries is -0.77, while it is only -0.31 and -0.24 for the linear and 50% quantile regression coefficients, respectively. For the 5% coefficients, we find that 47 out of 74 industries (that is, 63.5%) are significantly different from zero (based on the 95% bootstrap confidence bands), whereas for the linear regression and median coefficients this is the case for 49 industries (that is, 66.2%) and 41 industries (that is, 55.4%), respectively. By contrast, the 95% quantile regression coefficients display a mix of positive and negative values with an average value of 0.04, where only 5 industries (that is, 6.8%) have significant coefficients. Interestingly, the industries with large negative 5% coefficients seem to have large positive 95% coefficients as well, although this is most obvious for iron, motor vehicles, fiber and resin. Hence, industries with large downside production growth risk are also inclined to have more upside potential in times of tight financial conditions, which implies that their production growth volatility is higher during these period. Still, the upside potential is generally smaller than the increased downside risk.

Comparing Figures 2 and 3, we find that these effects seem to be stronger for the durable than for the nondurable goods sector. The average 5%, 50% and 95% NFCI quantile regression coefficients in the durable goods sector, given in Table 2, are -0.96, -0.31 and 0.03, respectively, while they are -0.48, -0.12 and 0.06 in the nondurable goods sector. Hence, industries in the durable goods sector are, on average, twice as sensitive in the left tail of the growth distribution to adverse financial conditions than industries in the nondurable goods sector. This result is consistent with the fact that the durable goods sector is generally more cyclical than the nondurable goods sector (Petersen and Strongin, 1996), albeit that we specifically focus on the role of financial conditions here. We obtain that 34 out of 45 durable goods producing industries (that is, 75.6%) have significant 5% coefficients, while this only holds for 13 out of 29 nondurable goods producing industries (that is, 44.8%). In addition, 82.2%, 71.1% and 8.9% of the durable goods producing industries have significant mean, median and 95% NFCI coefficients,

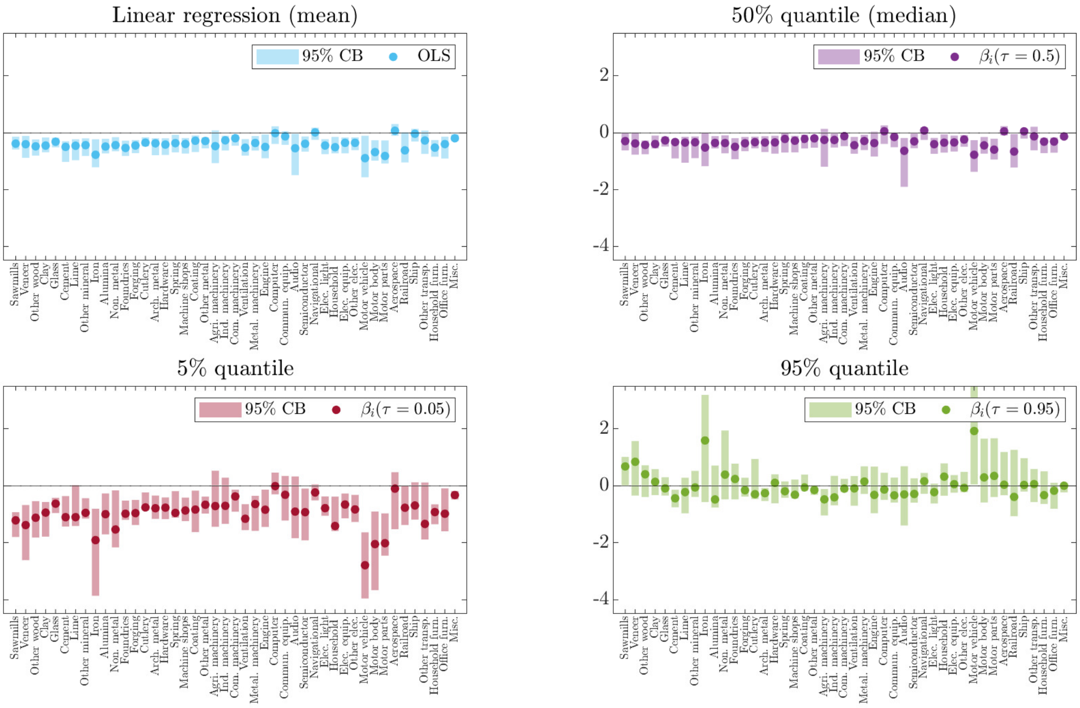

Figure 2: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for durable goods producing industries (with 95% bootstrap confidence bounds)

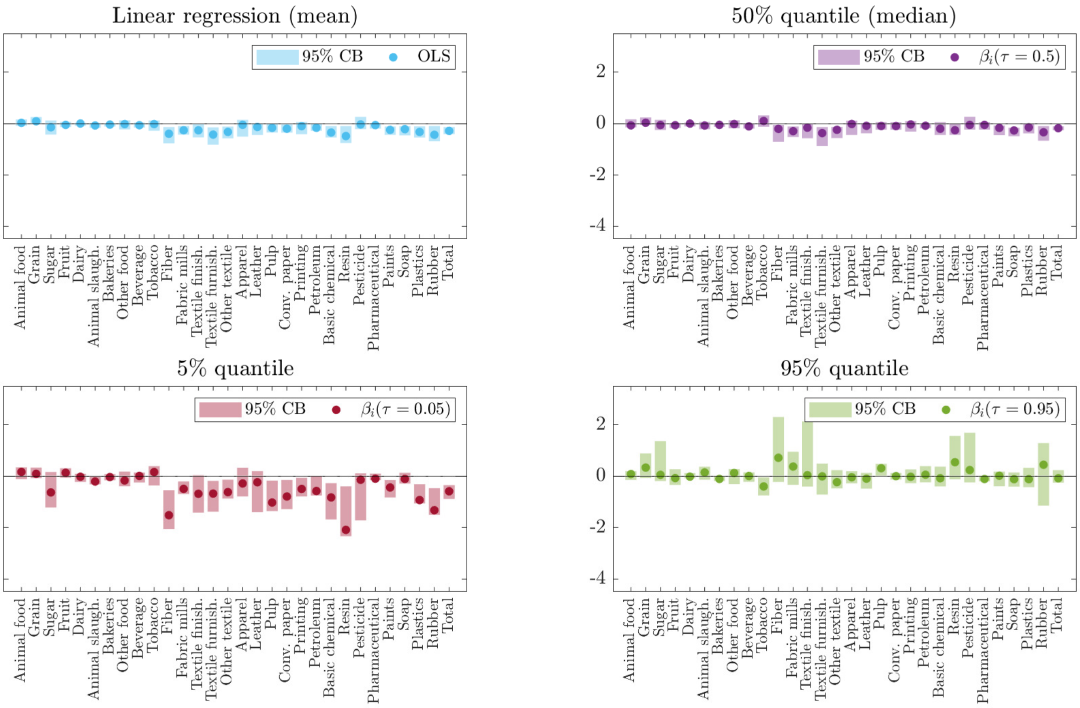

Figure 3: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for nondurable goods producing industries and the total manufacturing sector (with 95% bootstrap confidence bounds)

Table 2: Summary statistics of estimated linear and quantile NFCI regression coefficients

	Durables			Nondurables			All		
Quantile	**Mean**	**Std.**	**% sig.**	**Mean**	**Std.**	**% sig.**	**Mean**	**Std.**	**% sig.**
0.05	-0.96	0.52	75.6%	-0.48	0.54	44.8%	-0.77	0.57	63.5%
0.50	-0.31	0.18	71.1%	-0.12	0.11	31.0%	-0.24	0.18	55.4%
0.95	0.03	0.48	8.9%	0.06	0.24	3.4%	0.04	0.40	6.8%
Mean	-0.40	0.20	82.2%	-0.17	0.16	41.4%	-0.31	0.21	66.2%

Notes: This table shows the summary statistics of the estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for industries in the durable goods, nondurable goods and total manufacturing sector. We include the mean and standard deviation (std.) of the coeffients as well as the percentage of industries that have a significant coefficient (based on the 95% bootstrap confidence bands).

respectively, whereas this is the case for 41.4%, 31.0% and 3.4% of the nondurable goods producing industries. In sum, the durable goods sector is more affected by the NFCI than the nondurable goods sector.

The distinction between durable and nondurable goods is not the only relevant factor for differences in growth vulnerability. Within both subsets of industries, we observe substantial additional heterogeneity, see again Figures 2 and 3. For durables, for example, the downside production growth risk of motor vehicles, motor bodies, and motor parts are all strongly affected by the NFCI with significant 5% quantile regression coefficients below -2. In contrast, the 5% coefficients for the computer and aerospace industry are both insignificant. Similarly for nondurables, the downside growth risk of resin and fiber production is strongly affected by the NFCI with significant coefficients below -1.5, while the food industries are unaffected by financial market conditions. More generally, the standard deviations of the quantile regression coefficients across all industries are 0.57, 0.18 and 0.40 for the 5%, 50% and 95% quantiles, respectively. Comparing these dispersion measures with total manufacturing sector coefficients (which are equal to -0.59, -0.18 and -0.09 for the 5%, 50% and 95% quantiles, respectively) and the average industry coefficients, we can conclude that there is strong heterogeneity across the industries. For the durable goods sector, the standard deviations of the coefficients are 0.52 , 0.18 and 0.48 for the 5%, 50% and 95% quantiles, respectively, whereas they are 0.54 , 0.11 and 0.24 for the nondurable goods sector. Hence, there seems to be comparable levels of heterogeneity in the 5% quantile regression coefficient for the nondurable goods sector relative to the durable goods sector, while there is slightly less heterogeneity for the 50% and especially the 95% coefficients. Overall, it is apparent that some industries have more vulnerable production growth with respect to financial conditions than others.

The quantile regression coefficients corresponding to current IP growth ($\hat{\phi}_i(\tau)$) from equation (1) are given in Appendix G. Similarly as for the NFCI coefficients, we find substantial heterogeneity in these coefficients across industries, particularly the absolute magnitudes of the IP coefficients are larger for the durable goods sector than for the nondurable goods sector. Yet, we find less pronounced differences between the 5%, 50% and 95% coefficients, which implies a close to linear relationship between current and future IP growth.

To assess the effect of the NFCI on different parts of the distribution of three-month ahead IP growth more fully, we plot the estimated NFCI quantile regression coefficients across the quantiles $[0.05, 0.10, \ldots, 0.90, 0.95]$ in Figure 4 for a selection of 23 industries and the total manufacturing sector. Corresponding graphs of the other industries are shown in Appendix H. We also include the OLS estimates of the linear regression coefficients, which are, by nature, constant across quantiles, and the corresponding 95% confidence bounds based on 1,000 bootstrap samples. More specifically, these confidence bounds are based on the approach of Adrian et al. (2019) and correspond to the null hypothesis that the true data generating process is a VAR(4) process for the NFCI and IP growth, where the parameters are estimated based on the full sample. Consequently, quantile coefficient estimates that lie outside these confidence bands provide evidence of a nonlinear relationship between IP growth and the NFCI.

We find for a large number of industries (for example fiber, sawmills, rubber and motor parts) that the NFCI quantile coefficients are significantly different from the linear regression coefficient for quantiles in the left and/or right tails of the distribution. In fact, 46 of the 74 industries (that is, 62.2%) have a 5% quantile coefficient that is significantly different from the OLS estimate. As a result, the production growth rates of these industries all have a nonlinear relationship with the NFCI. We find that 35 of the 45 durable industries (that is, 77.8%) have significantly different 5% coefficients from the mean estimates, whereas this holds for only 11 of the 29 nondurable industries (that is, 37.9%). Hence, the industries in the durable goods sector are more prone to have a nonlinear relationship with the NFCI than the nondurable goods producing industries. The output growth of the total manufacturing sector also has a nonlinear relationship with the NFCI, which concurs with the results of Adrian et al. (2019) for aggregate

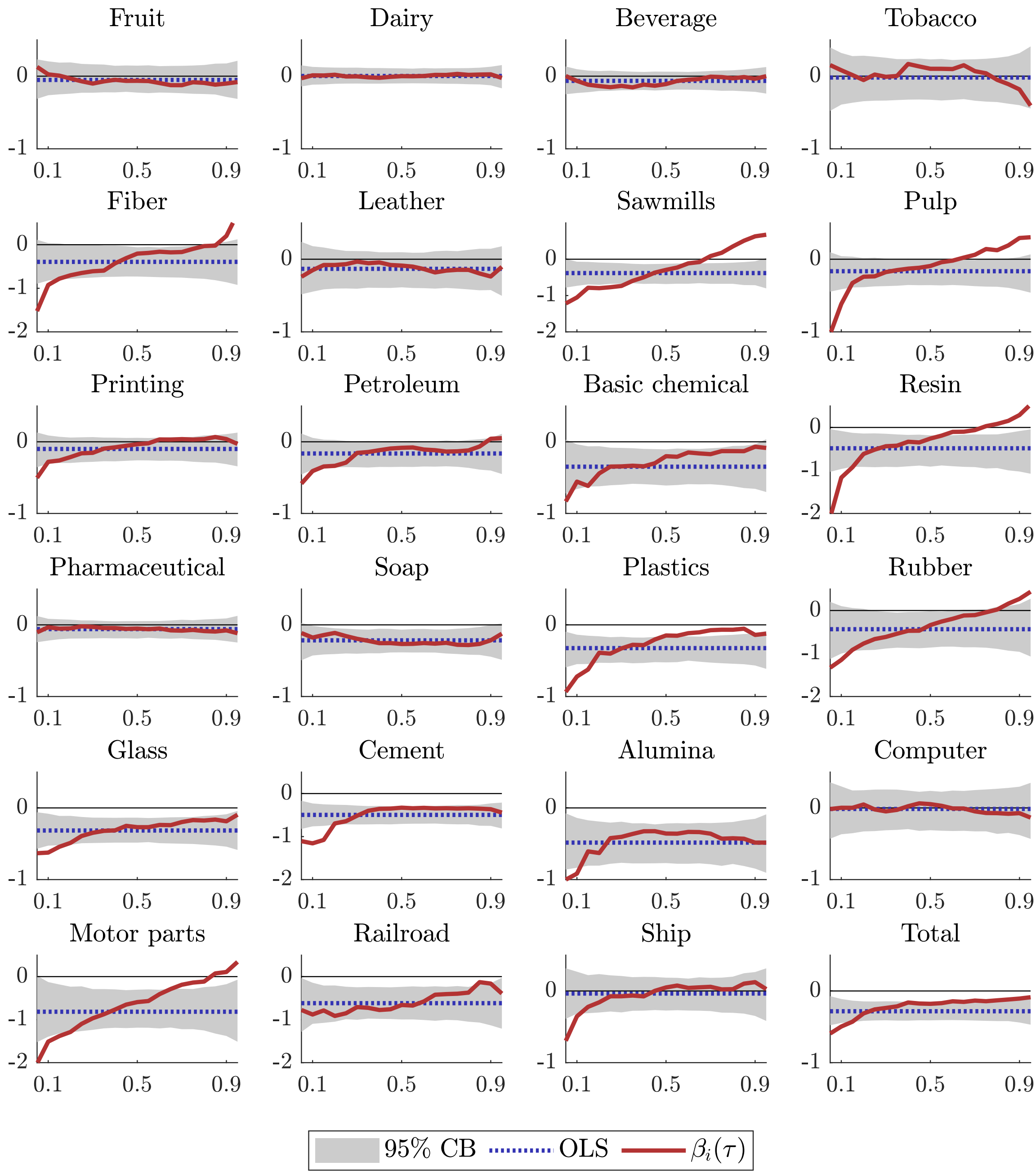

Figure 4: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) across quantiles (with 95% bootstrap confidence bounds based on a VAR(4) model for IP and NFCI as data-generating process) for a selection of 23 industries and the total manufacturing sector

GDP growth. Yet, for the other industries (for example dairy, leather and computers), the NFCI quantile regression coefficients are not significantly different from the linear regression coefficient. In fact, for most of these industries there seems to be no effect of the NFCI on any part of the distribution of future IP growth.

Lastly, we conduct a subsample analysis to examine how the industry-specific growth risks differ across various periods. Specifically, we split our sample into three parts: (i)

January 1973 - December 1984, (ii) January 1985 - December 2006, and (iii) January 2007 - July 2020. The first period corresponds to the more volatile period prior to the so-called Great Moderation in the second period, which has been characterized by a reduction in business cycle volatility, while the third period includes both the financial crisis of 2007-2008 and the onset of the corona virus pandemic. Figure 5 shows the 5% NFCI coefficients for both the industries in the durable and nondurable goods sectors across the three periods. Notably, for both sectors, the effects seem to be strongest for the most recent period with an average 5% coefficient of -1.38 compared to -0.73 and -0.49 for the first and second period, respectively. In fact, the coefficients are most negative for 50 out of 74 industries during the third period, which includes the financial crisis and the beginning of the pandemic. Meanwhile, the 5% coefficients are weakest during the Great Moderation period. Across all three periods, the coefficients are most negative for the durable goods sector, with average 5% coefficients of -0.93, -0.77 and -1.66 for the first, second and third period, respectively, compared to -0.41, -0.07 and -0.94 for the nondurable goods sector. Hence, the differences between the durables and nondurables are still observed for the subsamples.

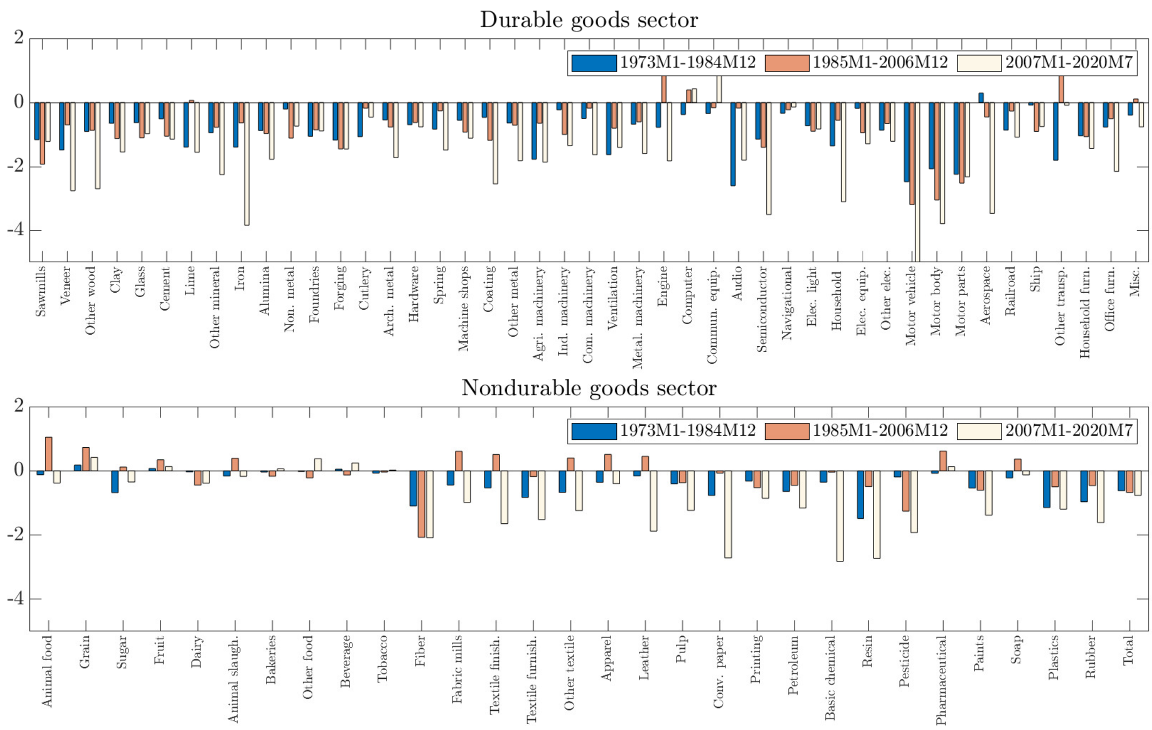

Figure 5: Estimated 5% quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for three different subsamples

4.2 Testing for slope homogeneity across industries

To formally test whether the quantile regression coefficients are significantly different across industries, we conduct the quantile slope homogeneity tests of Galvao et al. (2018). Specifically, they derive a Swamy-type test (Swamy, 1970) and a standardized Swamy-type test (Pesaran and Yamagata, 2008; Blomquist and Westerlund, 2013) for a quantile regression fixed effects panel data model. For further details on the specification of these tests, see Appendix I.

Table 3 shows the p-values corresponding to these slope homogeneity tests. For the durable and nondurable goods sectors, we find that the NFCI slope coefficients are significantly different across industries up to the 45% and 40% quantiles, respectively. Moreover,

Table 3: p-values of slope homogeneity tests across industries for the NFCI coefficients

	Durables		**Nondurables**		**All**	
Quantile	$\boldsymbol{S}$	$\boldsymbol{\Delta}$	$\boldsymbol{S}$	$\boldsymbol{\Delta}$	$\boldsymbol{S}$	$\boldsymbol{\Delta}$
0.05	0.00	0.00	0.00	0.00	0.00	0.00
0.10	0.00	0.00	0.00	0.00	0.00	0.00
0.15	0.00	0.00	0.00	0.00	0.00	0.00
0.20	0.00	0.00	0.00	0.00	0.00	0.00
0.25	0.00	0.00	0.00	0.00	0.00	0.00
0.30	0.00	0.00	0.00	0.00	0.00	0.00
0.35	0.01	0.01	0.00	0.00	0.00	0.00
0.40	0.02	0.04	0.02	0.03	0.00	0.00
0.45	0.01	0.01	**0.12**	**0.30**	0.00	0.00
0.50	0.04	**0.08**	**0.41**	**0.99**	0.00	0.00
0.55	**0.10**	**0.23**	**0.44**	**0.95**	0.00	0.00
0.60	**0.35**	**0.84**	**0.46**	**0.90**	0.01	0.01
0.65	**0.46**	**0.94**	**0.17**	**0.44**	0.00	0.00
0.70	**0.61**	**0.66**	**0.32**	**0.79**	0.02	0.04
0.75	**0.73**	**0.46**	**0.51**	**0.81**	**0.09**	**0.20**
0.80	**0.53**	**0.79**	**0.60**	**0.64**	**0.08**	**0.16**
0.85	**0.18**	**0.43**	**0.39**	**0.95**	0.03	0.05
0.90	**0.07**	**0.15**	**0.31**	**0.79**	0.02	0.04
0.95	**0.23**	**0.55**	**0.49**	**0.84**	**0.24**	**0.56**
Mean	0.00	0.00	0.00	0.00	0.00	0.00

Notes: This table shows the p-values of the Swamy (S) and standardized Swamy (Δ) slope homogeneity tests across industries for the NFCI coefficients at the horizon $h = 3$. The covariance matrix of the coefficients needed for the test is estimated using the stationary bootstrap approach discussed in section 2. A bluer (darker) shade indicates a higher p-value and hence less evidence of slope heterogeneity over the industries. A bold p-value indicates insignificance at the 5% level.

for the total manufacturing sector, there is clear evidence of heterogeneity for all quantiles, except 75%, 80% and 95%. Hence, this suggests that the significant heterogeneity between the 45% and 70% quantiles is due to differences in the durable and nondurable goods sectors. By comparing the Swamy and standardized Swamy tests, we see that the former is less conservative for all sectors, although their conclusions on significance are generally the same, except for the 50% quantile in the durable goods sector. The mean effects corresponding to the linear regression coefficients are significantly different across industries for all tests and sectors. Finally, we are able to conclude that the differences across U.S. manufacturing industries in how strongly they are affected by financial conditions are significant, particularly for lower quantiles, and we now turn to the question how these differences can be explained.

4.3 Heterogeneity in growth risk and industry characteristics

To examine which industry characteristics provide a signal for the extent of growth risk, we first take a look at the correlations of the NFCI coefficients with the industry characteristics in Table 4.

First, we discuss the correlations related to the total manufacturing sector. Here we find that the NFCI quantile regression coefficients are significantly correlated with capital and production labor intensity, labor hoarding and durability, except for the 95% quantile. In particular, the capital intensity and labor hoarding measure have a positive correlation, while the production labor intensity and durability dummy have a negative correlation. Indeed, this negative correlation of the durability dummy confirms our observed differences between the durable and nondurable goods sectors in Figures 2 and 3. We find similar correlation signs and significance patterns for the OLS estimates. The materials intensity is positively correlated with the 95% coefficient and value added with the 50% coefficients. On the other hand, energy intensity is negatively correlated with the 5% coefficient and overhead labor intensity with the 95% coefficient. The concentration ratio is uncorrelated with all coefficients.

Second, for the correlations based on the durable goods sector, we observe that the materials and overhead labor intensities both have significant correlations across all quantiles. Specifically, the materials intensity has a negative correlation for the 5% and 50% quantiles and a positive correlation for the 95% quantile, while it is the other way around

Table 4: Correlations of NFCI quantile and OLS coefficients with industry characteristics

Quantile	VA	Cap.	Mat.	Energy	ProdL	OverL	LH	CR	Dur.
Panel A: Total manufacturing sector (74 industries)									
0.05	0.08	**0.31**	-0.12	**-0.25**	**-0.46**	0.16	**0.55**	0.02	**-0.41**
0.50	**0.24**	**0.34**	-0.03	-0.11	**-0.41**	0.09	**0.53**	0.08	**-0.52**
0.95	0.16	-0.06	**0.32**	0.19	0.17	**-0.34**	-0.04	0.16	-0.05
Mean	**0.17**	**0.32**	-0.01	**-0.18**	**-0.46**	0.10	**0.62**	0.10	**-0.53**
Panel B: Durable goods sector (45 industries)									
0.05	0.04	-0.31	**-0.68**	-0.22	**-0.34**	**0.70**	**0.27**	-0.21	
0.50	0.20	-0.09	**-0.51**	-0.19	-0.27	**0.62**	**0.41**	-0.09	
0.95	0.28	0.34	**0.49**	0.11	0.22	**-0.40**	-0.04	0.19	
Mean	0.14	-0.16	**-0.53**	-0.24	**-0.33**	**0.71**	**0.45**	-0.09	
Panel C: Nondurable goods sector (29 industries)									
0.05	0.02	**0.36**	0.05	**-0.48**	**-0.41**	-0.14	**0.58**	**0.23**	
0.50	0.21	**0.45**	0.11	-0.16	**-0.35**	**-0.25**	**0.43**	0.28	
0.95	-0.29	-0.35	0.21	**0.48**	0.26	-0.19	-0.19	0.06	
Mean	0.09	**0.34**	0.14	-0.29	**-0.41**	**-0.23**	**0.61**	**0.27**	

Notes: This table shows the correlations of the NFCI quantile and OLS coefficients at the horizon $h = 3$ with the following industry characteristics: Value added (VA), capital intensity (Cap.), materials intensity (Mat.), energy intensity (Energy), production labor intensity (ProdL), overhead labor intensity (OverL), labor hoarding (LH), concentration ratio (CR) and durability dummy (Dur.). A green (dark) shade indicates high positive correlations, a red (dark) shade indicates high negative correlations, and white (no shade) indicates no strong correlation. A bold value indicates significance at the 5% level.

for the overhead labor intensity. Furthermore, the production labor intensity and labor hoarding measure have a significant correlation with the 5% quantile coefficient, while the latter is also correlated with the 50% quantile. Hence, there are generally more industry characteristics that correlate with the lower quantiles. For the OLS coefficients, we find correlation signs that are consistent with the predicted cyclicality relationships of Petersen and Strongin (1996). That is, a positive correlation with the NFCI coefficient corresponds to a negative correlation with their cyclicality measure, and vice versa.

Third, the nondurable goods sector has smaller correlation magnitudes for the materials and overhead labor intensities than the durable goods sector. Nonetheless, both labor hoarding and the capital intensity are positively and significantly correlated with the NFCI coefficients for the 5% and 50% quantiles, while the energy and production labor intensity are negatively correlated. Interestingly, the capital intensity is positively correlated in the nondurable goods sector, while it was negatively correlated in the durable goods sector, albeit not significant. The OLS coefficients are significantly correlated with the capital, production and overhead labor intensities, labor hoarding measure and the concentration ratio.

We now turn to the second-level regression results based on equation (3), where the NFCI coefficients are linked to the industry characteristics.[16] Figure 6 shows the estimated industry-characteristic effects ($\hat{\delta}_k(\tau)$) on the NFCI coefficients across quantiles based on all 74 industries in the manufacturing sector with the corresponding 95% bootstrap confidence intervals that account for the estimation uncertainty from the first level. First, we find that the intercept is negative for almost all quantiles, where the magnitude of the intercept becomes larger for lower quantiles. Hence, for average values of all industry characteristics (that is, a value of zero due to the standardization of the characteristics) the NFCI quantile regression coefficient becomes more negative for lower quantiles and hence implies a nonlinear average relationship between the NFCI and manufacturing output growth. This indeed agrees with our findings in Figures 2 and 3, and the fact that over 60% of all industries have a significant nonlinear relationship with the NFCI.

Second, we find significant negative effects of industry size (as measured by value added) and the durability dummy on lower quantile NFCI coefficients, albeit the latter is also significant for central quantiles. This means that the downside production growth of large or durable goods producing industries is, on average, more vulnerable to adverse

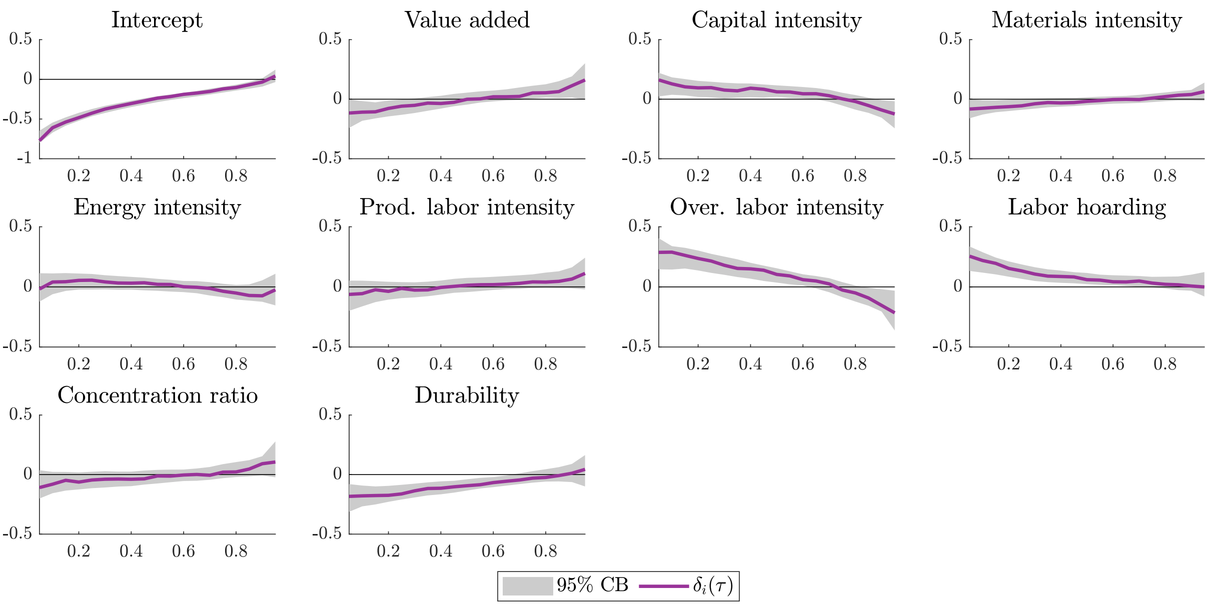

Figure 6: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles based on all 74 industries in the manufacturing sector (with 95% bootstrap confidence bounds)

[16] The complete tables with estimated regression coefficients and R^2's are given in Appendix J.

financial conditions than for small or nondurable goods producing industries. A possible reason that larger industries have more vulnerable growth is due to mean reversion (Braun and Larrain, 2005). In particular, if an industry is larger than the average size of the manufacturing industries, then its growth is more likely to fall. The effect of the durability dummy, on the other hand, is due to the fact that durable goods production is more cylcical than nondurable goods production (Petersen and Strongin, 1996).

Third, the effects of the overhead labor intensity and labor hoarding measure on the NFCI coefficients are both positive for lower and central quantiles, although the effect is less strong for the labor hoarding measure. In other words, the downside production growth of overhead labor intensive industries or industries engaging in labor hoarding is, on average, less vulnerable to financial conditions. This agrees with the explanation that industries that practice labor hoarding retain their trained employees and hence have a lower incentive to reduce production during a recession, or, in our case, during tight financial conditions. Similarly, nonproduction workers corresponding to overhead labor require, on average, more investments in terms of hiring and training (Parsons, 1986) than production workers, and therefore they are more eligible for labor hoarding. Hence, we obtain the positive effect of the overhead labor intensity.

Lastly, capital intensity also has a positive effect on lower quantile NFCI coefficients such that capital intensive industries are, on average, less vulnerable to financial conditions. One explanation for this observation is that capital intensive industries have higher fixed costs relative to variable costs such that they have less incentives to reduce production. In addition, industries with a high capital intensity can provide more collateral assets that could serve as protection for loans. Indeed, Braun and Larrain (2005) show that, among high external finance dependent industries, low capital intensity industries with less tangible assets are more affected by a recession than high capital intensity industries with more tangible assets. Note that all other industry characteristics are generally not significant in the analysis based on all 74 manufacturing industries.

Next, we consider the estimated industry-characteristic effects based on the 45 industries in the durable goods sector in Figure 7. We again find that the intercept is negative for all quantiles and becomes more negative for lower quantiles. Furthermore, industry size still has a significant, albeit small, negative effect on lower quantile NFCI coefficients in the durable goods sector, whereas the overhead labor intensity still has a positive

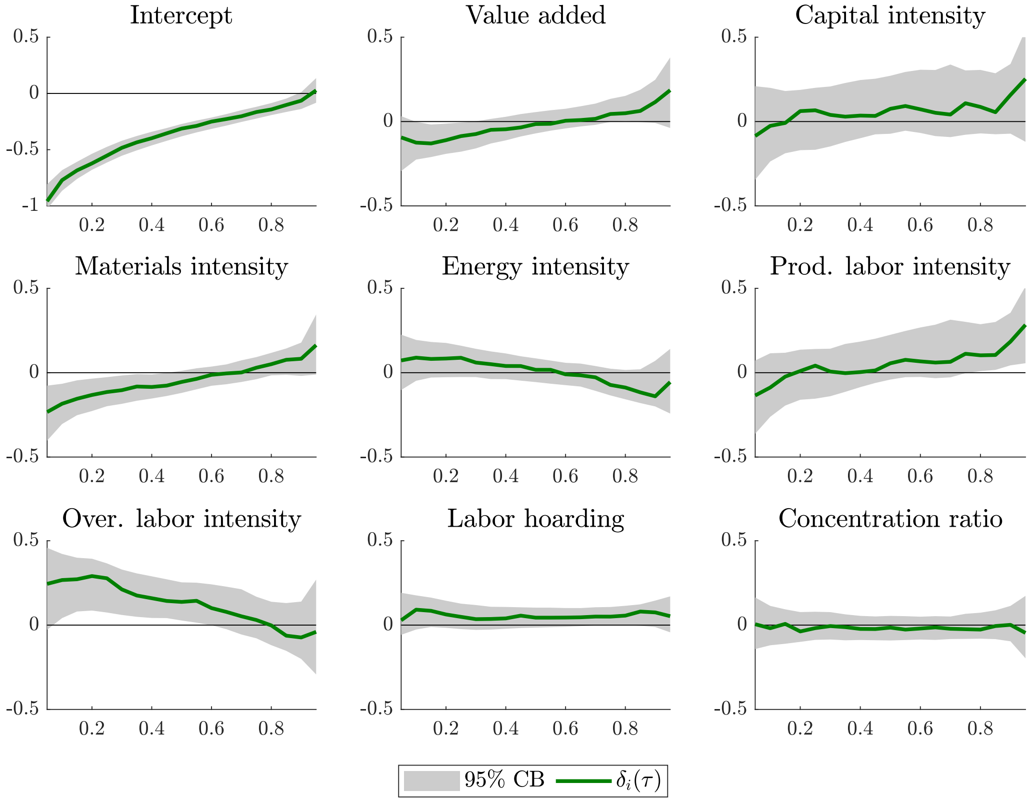

Figure 7: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the durable goods sector (with 95% bootstrap confidence bounds)

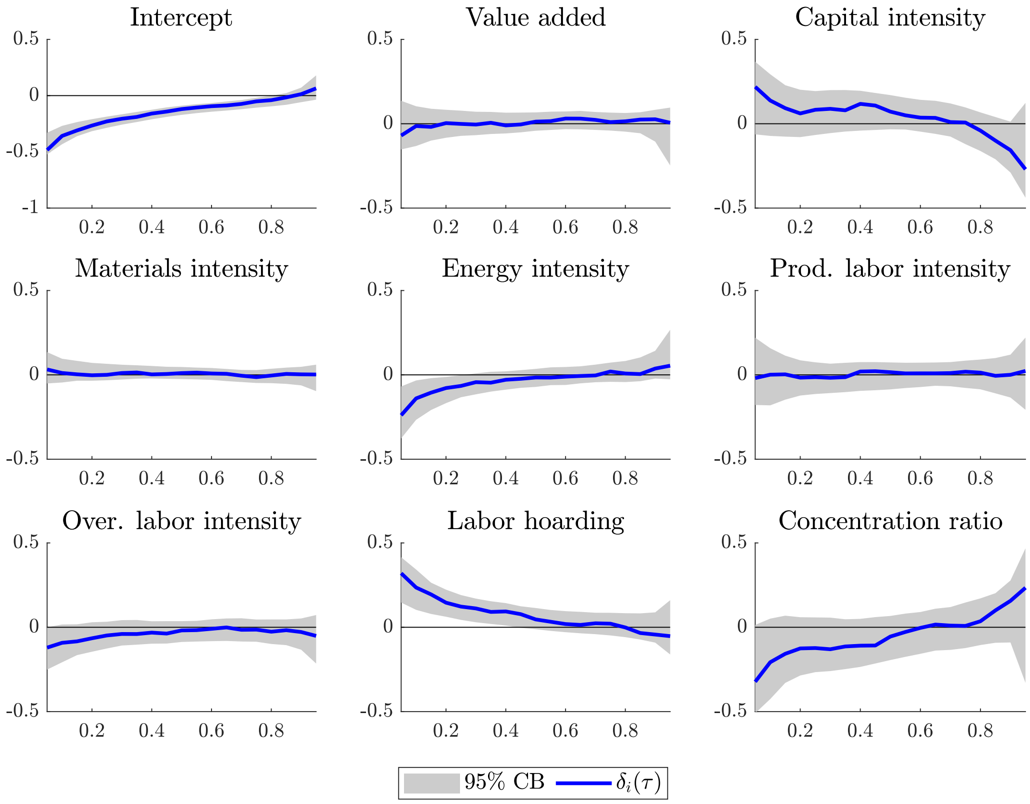

Figure 8: Estimated industry characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the nondurable goods sector (with 95% bootstrap confidence bounds)

effect. In other words, large durable goods producing industries have more vulnerable growth, while overhead labor intensive durable goods producing industries are less vulnerable. Notably, we also find a significant negative effect of the materials intensity on lower quantile NFCI coefficients. Hence, material intensive durable goods producing industries have more downside production growth risk in times of tight financial conditions. This finding complements the results of Baptist and Hepburn (2013), who show that there is a negative relationship between materials intensity and total factor productivity, where we show that there also exists a negative relationship between the materials intensity and production growth, at least for the durable goods sector. All other industry characteristics are insignificant across the complete range of quantiles, except that the production labor intensity is significant for some higher quantiles.

Moving to the industry effects based on the 29 industries in the nondurable goods sector in Figure 8, we find that the intercept is still negative across almost all quantiles, although less strong than for the durable goods sector. Moreover, the energy intensity has a significant negative effect now for lower quantiles, while the labor hoarding measure has a significant positive effect. This implies that energy intensive nondurable goods producing industries are more vulnerable, whereas labor hoarding intensive nondurable goods producing industries are less susceptible. The other industry characteristics are insignificant across the whole range of quantiles. It is interesting to note that we find less significant and different effects after the separation into the durable and nondurable goods sectors. Obviously, this could be due to the smaller cross-section of industries in both sectors, which makes it harder to find evidence against the null hypothesis of no industry-characteristic effect.

Finally, we consider three distinct subsamples in which the industry characteristics are constructed and averaged to assess the robustness of our findings to potential changes in the structure of the U.S. economy. Similarly as in section 4.1, we split the annual observations in a period before (1973-1984), during (1985-2006) and after (2007-2018) the Great Moderation. Figure 9 shows the corresponding industry-characteristic effects of regressing the full-sample industry-specific growth risk measures (from Figures 2 and 3) on the characteristics based on the three different subsamples. Recall that the capital intensity is not available before 1987 and the concentration ratio is only available for the years 2002, 2007 and 2012. In general, the effects seem to be relatively stable across

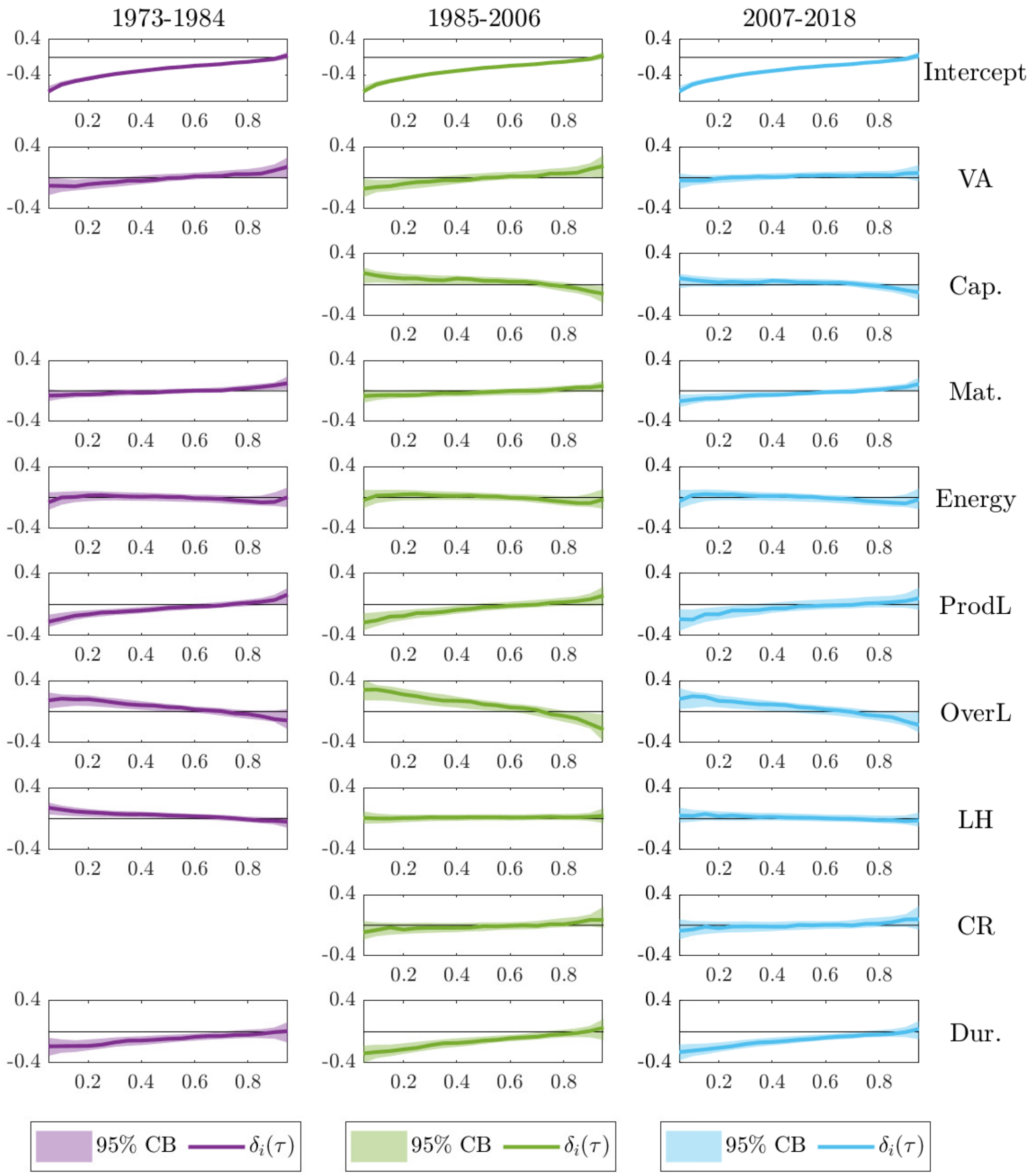

Figure 9: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles based on all 74 industries in the manufacturing sector (with 95% bootstrap confidence bands) for three subsamples used to construct and average the industry characteristics

the three subsamples, although the effects of industry size and labor hoarding become less strong for the more recent periods. Yet, the overhead labor intensity and durability dummy remain significant across all periods. Interestingly, the production labor intensity also has a negative and significant effect for the three subsamples, which was not the case for the complete sample in Figure 6. Indeed, the starting period analysis in Appendix E.2

indicates that leaving out the industry characteristic data before 1987 strengthens the negative effect of the production labor intensity. Still, the other characteristics remain insignificant across the different subsamples.

5 Conclusions

In this paper we document substantial heterogeneity in the sensitivity of output growth risk to financial market conditions across U.S. manufacturing industries. Using a multi-level quantile regression approach, we analyze how this heterogeneity can be explained by industry characteristics such as production input factors and labor hoarding. In particular, we employ industry-specific quantile regressions to link output growth risk with current financial and economic conditions, after which we link the corresponding quantile regression coefficients to industry characteristics. By doing so, our modelling approach allows for differences in growth vulnerability across industries and a way to explain these differences.

Our results show that it is indeed important to allow for heterogeneity in downside production growth risks across industries. In particular, we find significant differences in how strongly output growth risk is affected by financial conditions, where some industries seem to have a strong nonlinear relationship while other industries are unaffected. Moreover, we show that part of these differences can be explained by industry characteristics. Specifically, large or durable goods producing industries have more vulnerable growth, whereas capital and overhead labor intensive industries as well as industries engaging in labor hoarding have less vulnerable growth. Additionally, the materials and overhead labor intensities are important features to explain the differences in downside growth risk in the durable goods sector, whereas labor hoarding and the energy intensity are relevant for the nondurable goods sector.

From a practical point of view, these findings will help policy makers to identify which industries are more at risk and, particularly, why these industries are more at risk. At the same time, it provides investors with a straightforward approach to gain additional insights in the strengths and weaknesses of industries to construct a well-diversified industry-rotation strategy in the manufacturing sector.

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Heterogeneity in Manufacturing Growth Risk

Online Appendix

Daan Opschoor   Dick van Dijk   Philip Hans Franses

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Contents

A Controlling for additional variables

Beside the quantile regression approach of Adrian et al. (2019), we also consider a more extensive quantile regression with additional control variables taken from Gilchrist and Zakrajšek (2012) (henceforth GZ). More specifically, we add additional lags of $y_{i,t}$ and four macro-financial variables, namely the term spread (TS), real federal fund rate ($RFFR$), credit spread (CS) measure of GZ and the excess bond premium (EBP) measure of GZ. The corresponding τth quantile of $\bar{y}_{i,t+h}$ conditional on these variables is given by

$$Q_{\bar{y}_{i,t+h}|\boldsymbol{x}_{i,t},\boldsymbol{m}_t}(\tau|\boldsymbol{x}_{i,t},\boldsymbol{m}_t) = \alpha_i(\tau) + \beta_i(\tau)NFCI_t + \sum_{k=0}^{p-1}\phi_{i,k}(\tau)y_{i,t-k} + \boldsymbol{\kappa}_i(\tau)'\boldsymbol{m}_t,$$

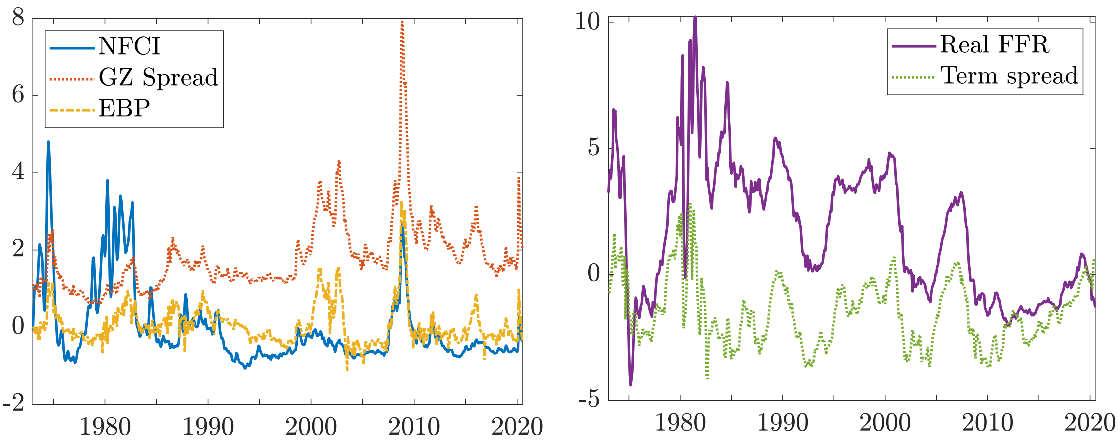
for $t = 1, \ldots, T-h-p+1$ and industries $i = 1, \ldots, N$, where we set the lag length equal to $p = 3$ and $\boldsymbol{m}_t = \big(TS_t, RFFR_t, CS_t, EBP_t\big)'$.

We obtain the term spread, defined as the difference between the 3-month and 10-year Treasury constant maturity yields, effective federal funds rate and core Personal Consumption Expenditure (PCE) price index series from the Federal Reserve Bank of St. Louis.[1] We follow Gilchrist and Zakrajšek (2012) and obtain the real federal funds rate as the effective federal funds rate minus the year-on-year changes of the core PCE index. Furthermore, we obtain the credit spread and excess bond premium (EBP) measures proposed in Gilchrist and Zakrajšek (2012) again from the Federal Reserve.[2] The time series are given in Figure A.1.

Figures A.2 and A.3 show the estimated linear and quantile regression coefficients with the 95% bootstrap confidence bounds after controlling for the GZ variables, where the coefficients are qualitatively similar as for the baseline regressions of Adrian et al. (2019) (which are indicated by the black crosses). Furthermore, Figures A.4, A.5 and A.6 show the industry characteristic effects with the 95% bootstrap CB and we again find qualitatively similar results as for the baseline model, although the confidence bands are generally wider and the intercepts are slightly higher in the total manufacturing and durable goods sectors. In sum, controlling for additional lags and macro-financial variables does not lead to drastic differences compared to the baseline model.

[1]The TS, FFR and core PCE series are obtained from `https://fred.stlouisfed.org/`

[2]The CS and EBP series are obtained from `https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html`



(a) Financial conditions **(b)** Stance of monetary policy

Figure A.1: Time series of U.S. financial conditions and the stance of monetary policy over the period January 1973 to July 2020

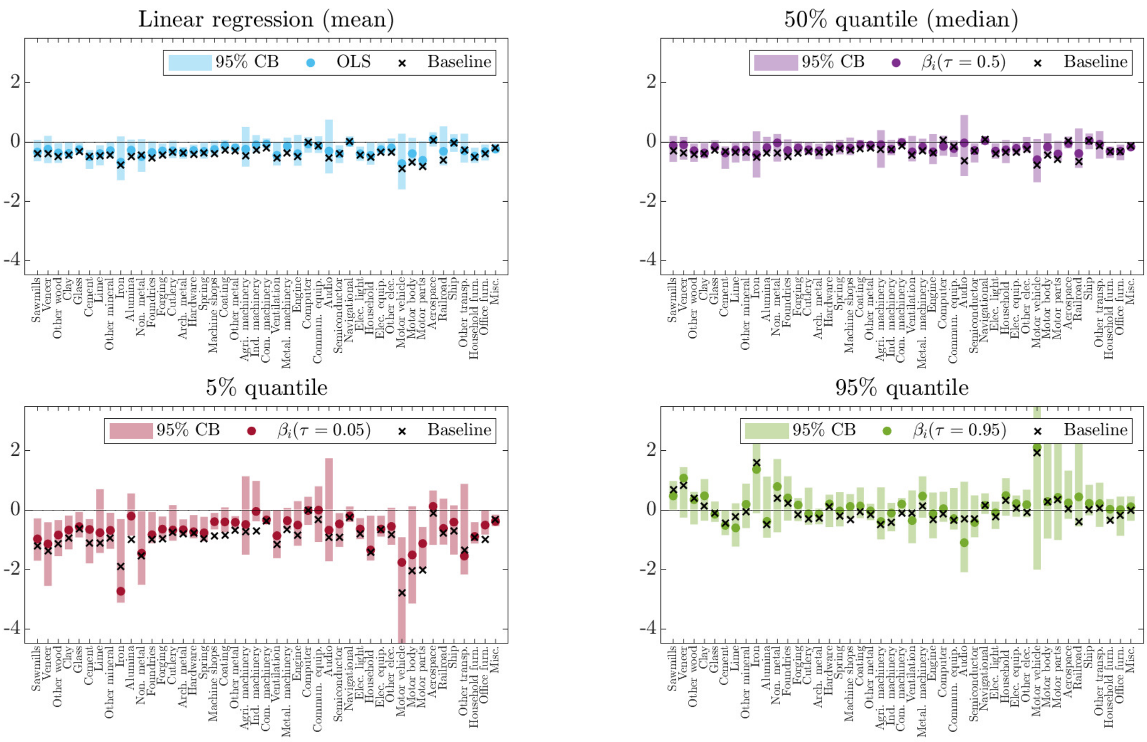


Figure A.2: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) after controlling for GZ variables for the durable goods sector (with 95% bootstrap confidence bounds)

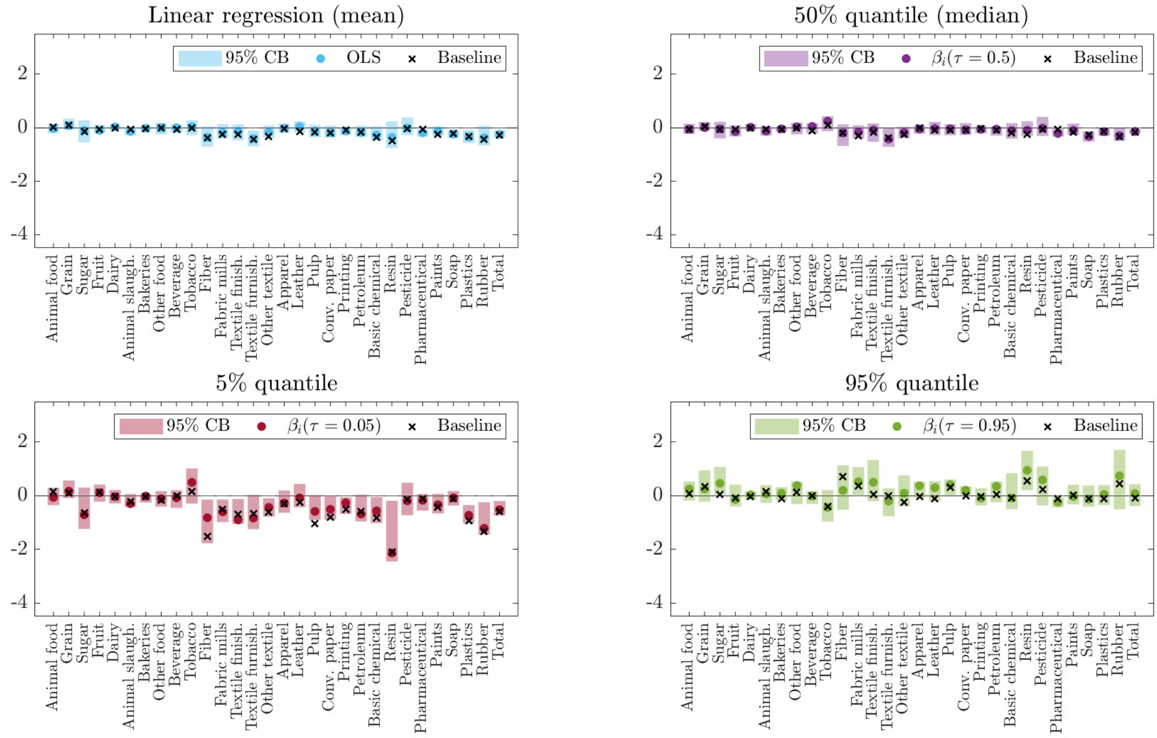


Figure A.3: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) after controlling for GZ variables for the nondurable goods sector (with 95% bootstrap confidence bounds)

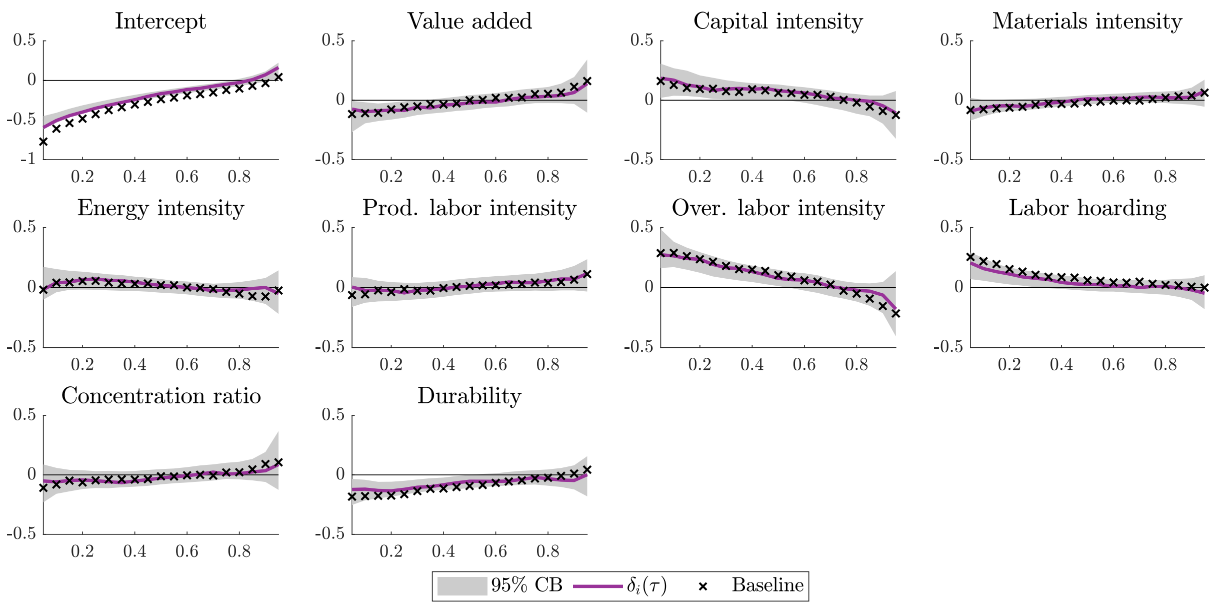


Figure A.4: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for GZ variables based on $h = 3$ across quantiles for the total manufacturing sector (with 95% bootstrap confidence bounds)

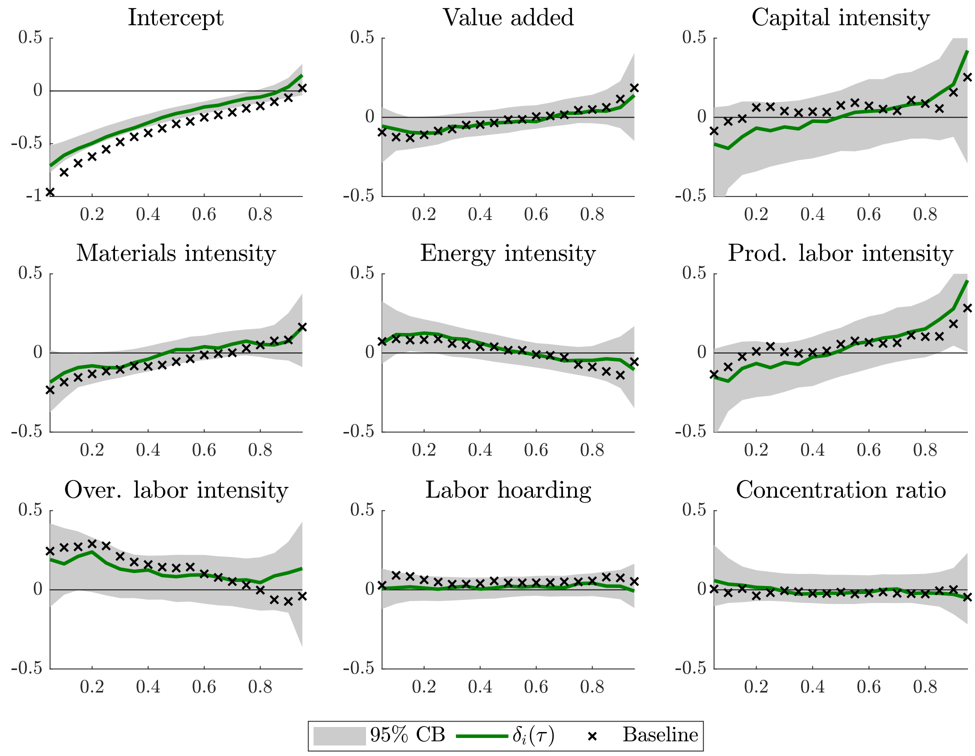


Figure A.5: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for GZ variables based on $h = 3$ across quantiles for the durable goods sector (with 95% bootstrap confidence bounds)

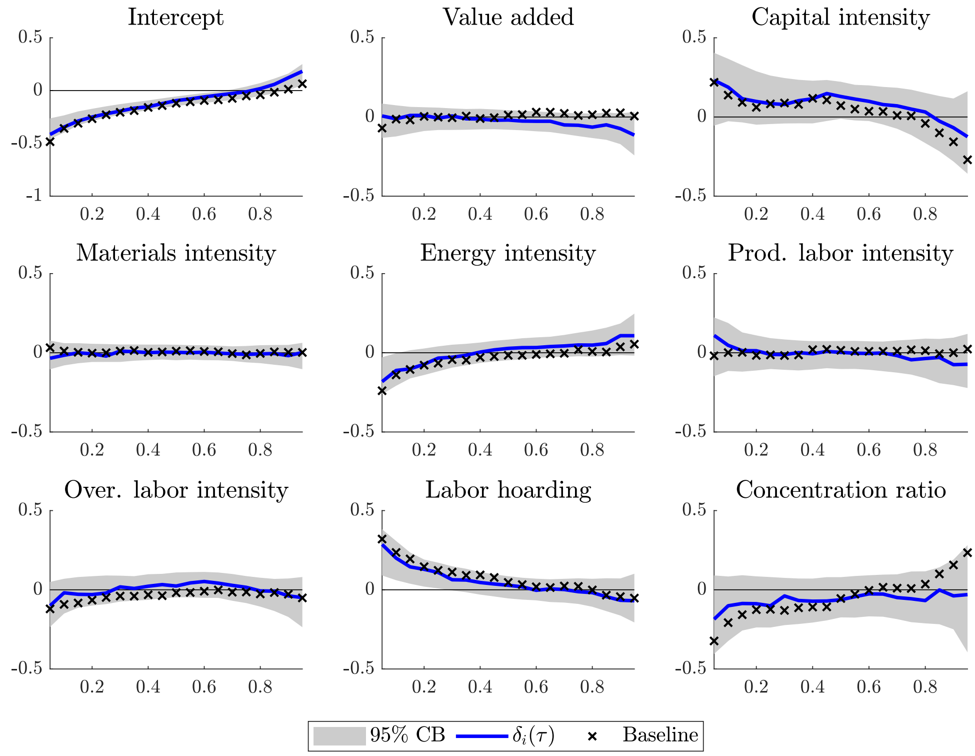


Figure A.6: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for GZ variables based on $h = 3$ across quantiles for the nondurable goods sector (with 95% bootstrap confidence bounds)

B Controlling for unobserved heterogeneity

To allow for unobserved heterogeneity, we also consider the heterogeneous panel quantile regression model with interactive fixed effects of Ando and Bai (2020). Specifically, the τth quantile of $\bar{y}_{i,t+h}$ conditional on $\boldsymbol{x}_{i,t}$ and the latent factor structure is given by

$$Q_{\bar{y}_{i,t+h}}(\tau|\boldsymbol{x}_{i,t}, \boldsymbol{\lambda}_i(\tau), \boldsymbol{f}_t(\tau)) = \alpha_i(\tau) + \beta_i(\tau)NFCI_t + \phi_i(\tau)y_{i,t} + \boldsymbol{\lambda}_i(\tau)'\boldsymbol{f}_t(\tau),$$

for $t = 1, \ldots, T-h$ and industries $i = 1, \ldots, N$, where $\boldsymbol{f}_t(\tau)$ and $\boldsymbol{\lambda}_i(\tau)$ are $r(\tau) \times 1$ vectors with unobservable quantile-dependent factors and factor loadings, respectively. We follow the frequentist estimation approach proposed in Ando and Bai (2020) to jointly estimate $\alpha_i(\tau)$, $\beta_i(\tau)$, $\phi_i(\tau)$ and $\boldsymbol{\lambda}_i(\tau)$ for $i = 1, \ldots, N$ and $\boldsymbol{f}_t(\tau)$ for $t = 1, \ldots, T-h$. Moreover, for each τ, we select $r(\tau)$ that minimizes the information criterion proposed by Ando and Bai (2020), where the maximum number of common factors is set to 12. We find for all quantiles that one common factor is optimal. For the heterogeneous mean panel data model with interactive fixed effects, we follow the estimation procedure of Song (2013) with the information criteria from Bai and Ng (2002), where one common factor is again optimal. As the estimation procedures of these heterogeneous panel data models are more computationally intense, especially for the panel quantile regression models, we do not consider a bootstrap approach to obtain the confidence bands of these estimators here.

Figures B.1 and B.2 show the linear and quantile regression coefficients after controlling for unobserved heterogeneity via the panel data models. The obtained coefficients are highly similar as the ones of the baseline model without interactive fixed effects (which are indicated by the black crosses), particularly for the mean and median coefficients. Moreover, Figures B.3, B.4 and B.5 display the industry characteristic effects after controlling for unobserved heterogeneity, where we again find very similar effects as for the baseline model of Adrian et al. (2019).

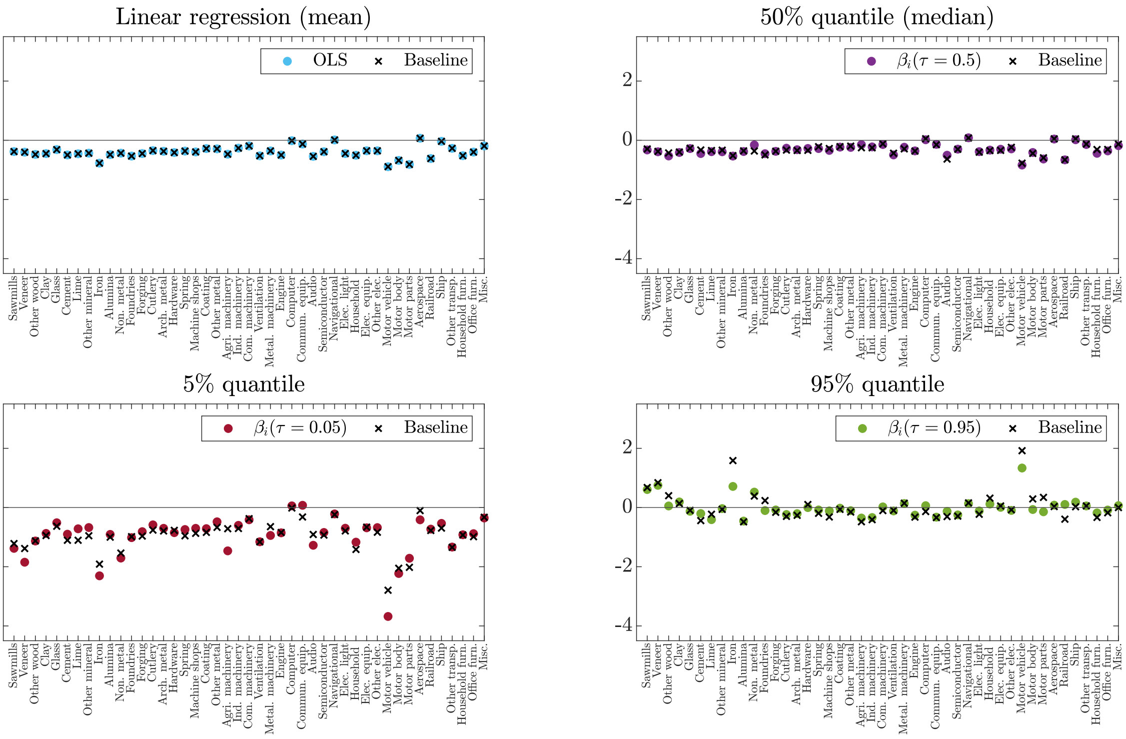


Figure B.1: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) after controlling for unobserved heterogeneity for the durable goods sector

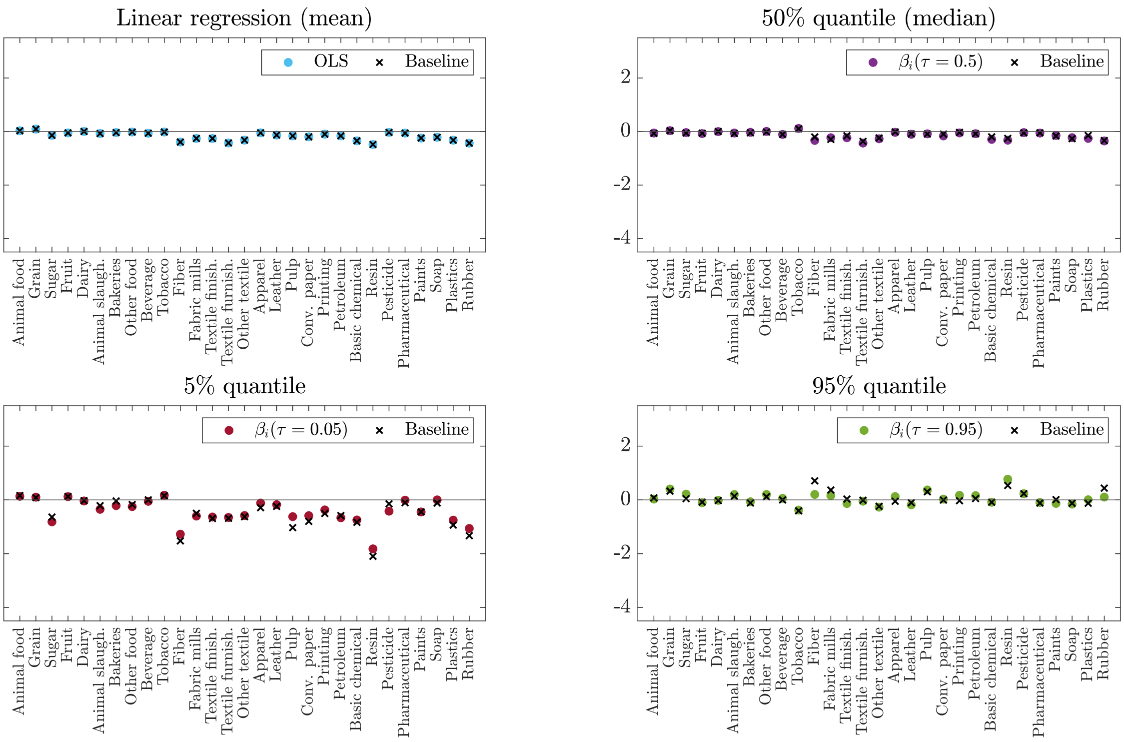


Figure B.2: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) after controlling for unobserved heterogeneity for the nondurable goods sector

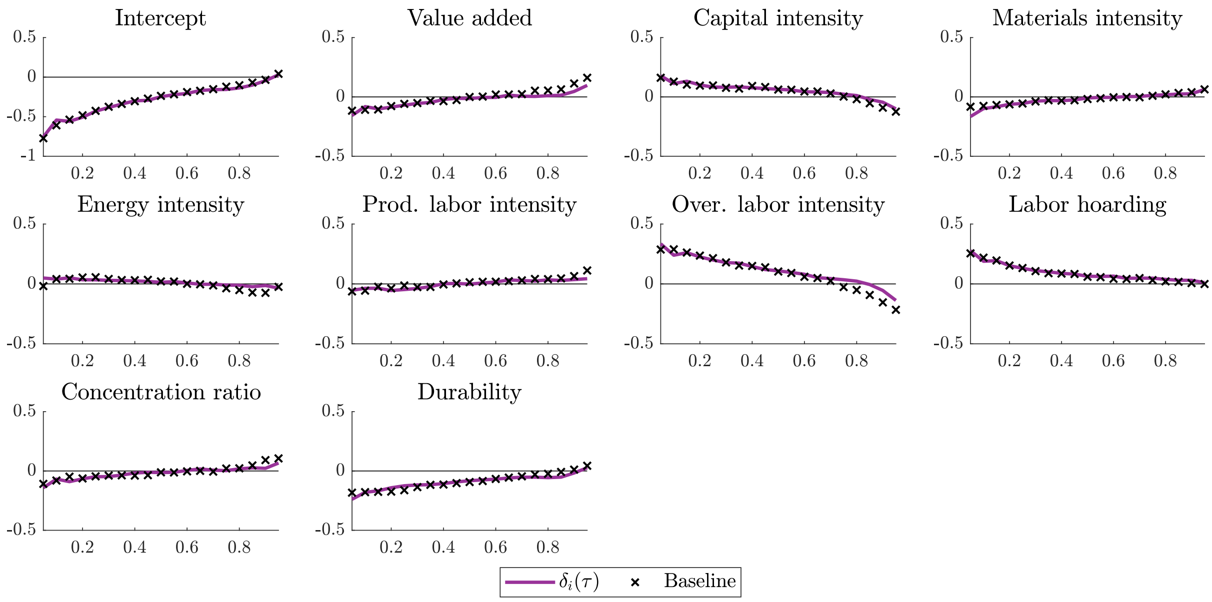


Figure B.3: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for unobserved heterogeneity based on $h = 3$ across quantiles for the total manufacturing sector

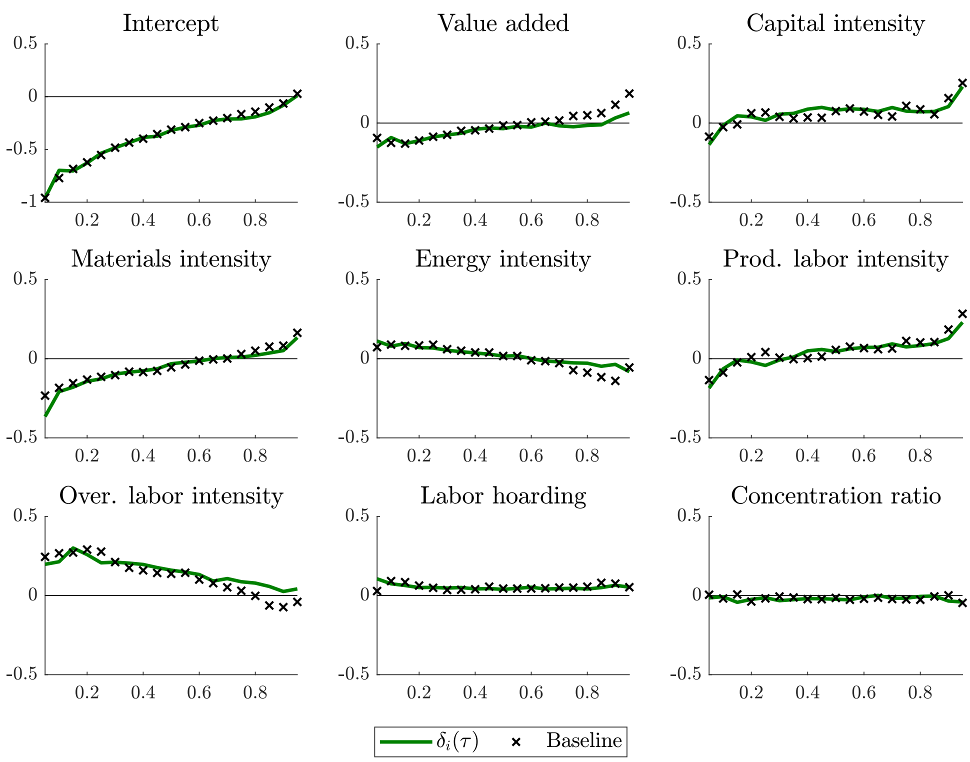


Figure B.4: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for unobserved heterogeneity based on $h = 3$ across quantiles for the durable goods sector

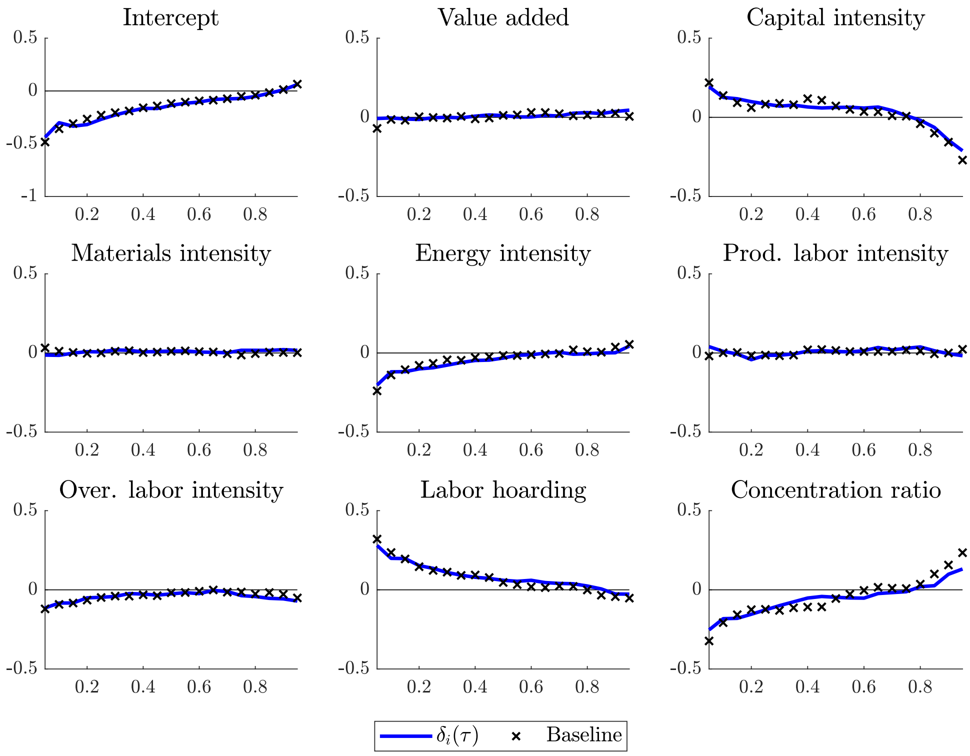


Figure B.5: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for unobserved heterogeneity on $h = 3$ across quantiles for the nondurable goods sector

C Alternative NAICS disaggregation levels

C.1 Three-digit NAICS level

Figure C.1 displays the linear and quantile NFCI regression coefficients for 21 three-digit NAICS level industries and the total index. Similarly as for the four-digit NAICS, we find that there is a clear asymmetric effect, where the 5% quantile coefficients are more negative than the linear and median coefficients. Next, Figure C.2 shows the corresponding industry-characteristic effects on these NFCI coefficients at the three-digit NAICS level. Note that we removed the capital intensity due to multicollinearity issues (see Appendix E.3). We find that only the labor hoarding measure and durability dummy are significant for lower quantiles with a similar sign as for the four-digit NAICS level, where all other characteristics are insignificant. This insignificance compared to the four-digit case could be due to the fact that we have a much smaller cross-section of only 21 industries, which makes it harder to find statistical evidence against no industry-characteristic effects.

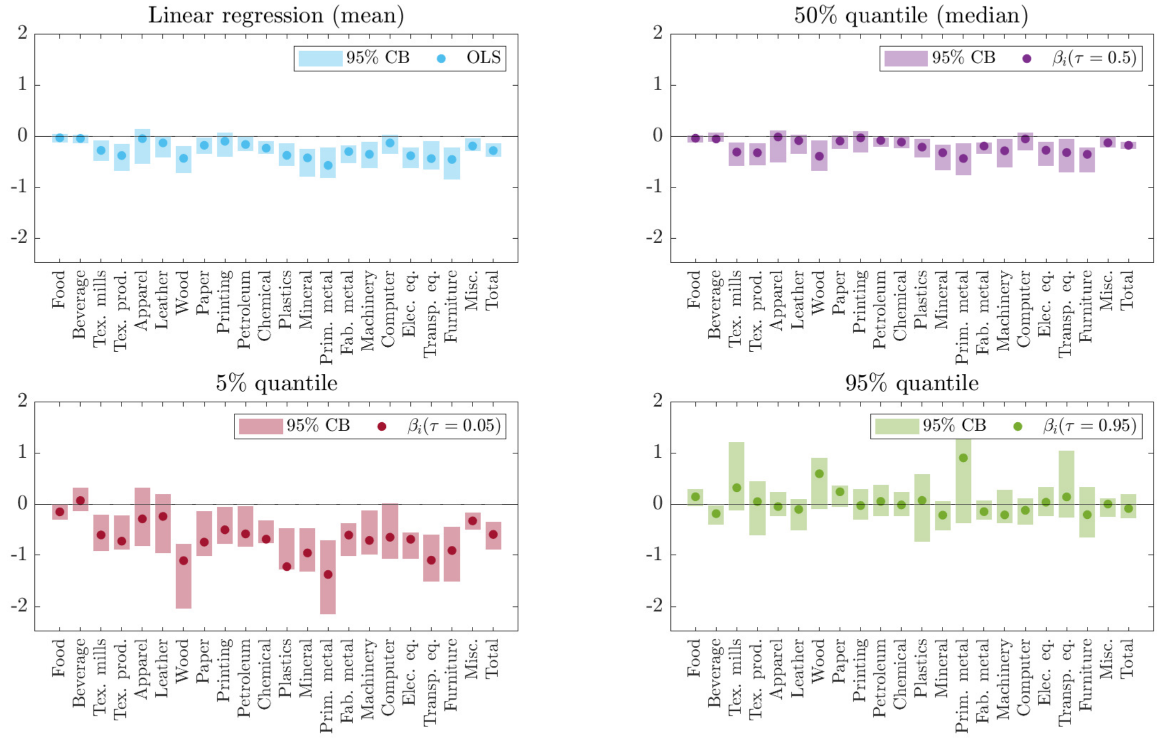


Figure C.1: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for the total manufacturing sector at the three-digit NAICS level (with 95% bootstrap confidence bounds)

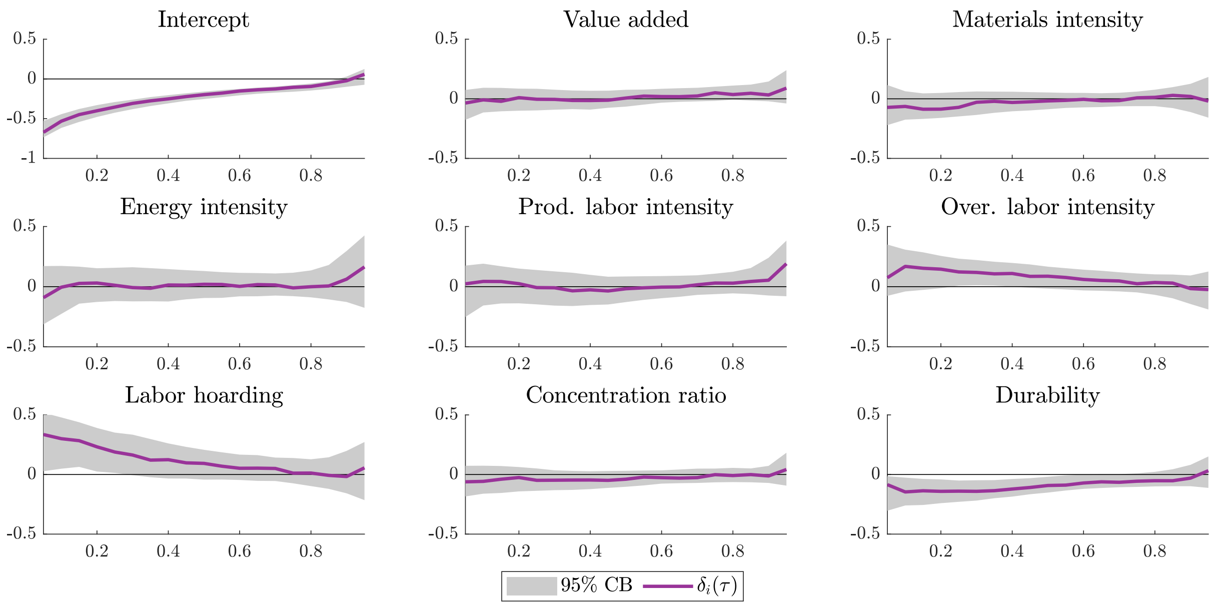


Figure C.2: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the total manufacturing sector at the three-digit NAICS level (with 95% bootstrap confidence bounds)

C.2 Six-digit NAICS level

Figures C.3 and C.4 show the linear and quantile regression NFCI coefficients for industries at the six-digit NAICS level. Similarly as for the four-digit level, we find asymmetric effects by comparing the 5% quantile and central quantile effects, where these effects are stronger for the durables than for the nondurables. Moreover, Figures C.5, C.6 and C.7 show the industry-characteristic effects at the six-digit NAICS level. Note that the capital intensity is not included as it is not available at the six-digit NAICS level. Based on the total manufacturing sector, we find significant effects for the overhead labor intensity, labor hoarding measure and durability dummy, just as for the four-digit case. However, for low quantiles, we also find significant effects for the production labor intensity and concentration ratio, which was not the case for the four-digit level. This might come from the larger cross-section, which can provide more evidence against no characteristic effects. Nonetheless, for the durable and nondurable good sectors, we find similar results as for the four-digit NAICS level, except that the materials intensity is now significant at the six-digit level for the nondurables.

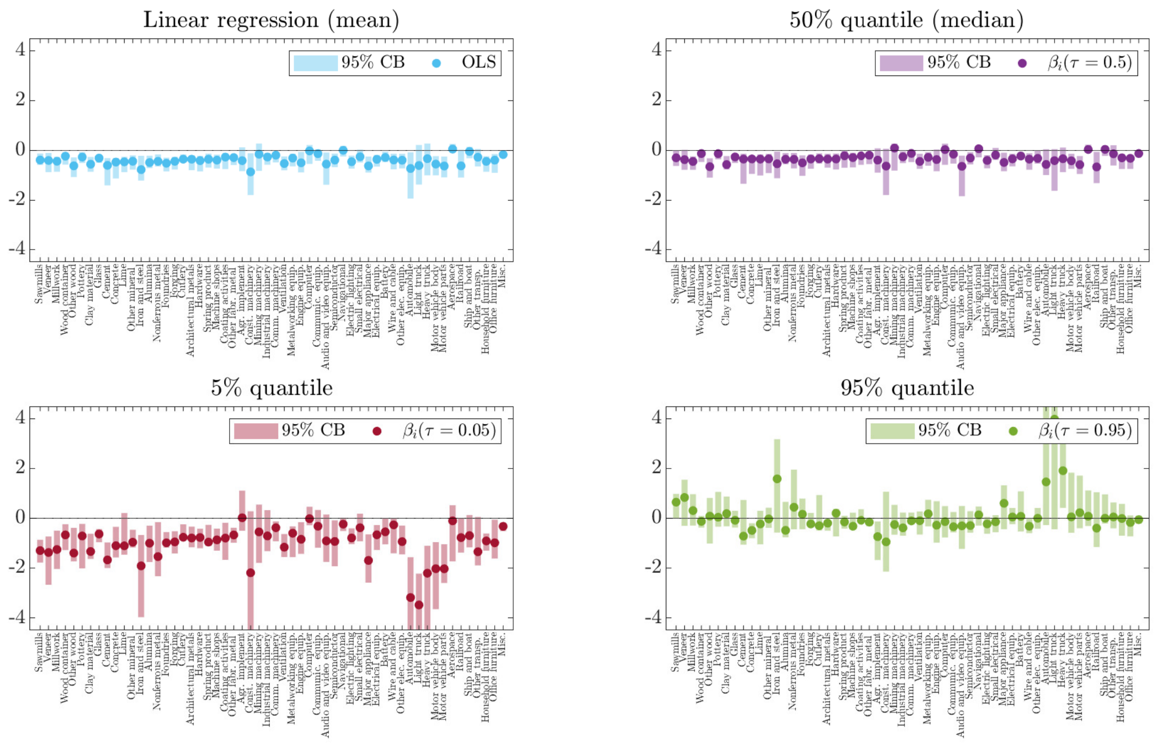


Figure C.3: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for the durable goods sector at the six-digit NAICS level (with 95% bootstrap confidence bounds)

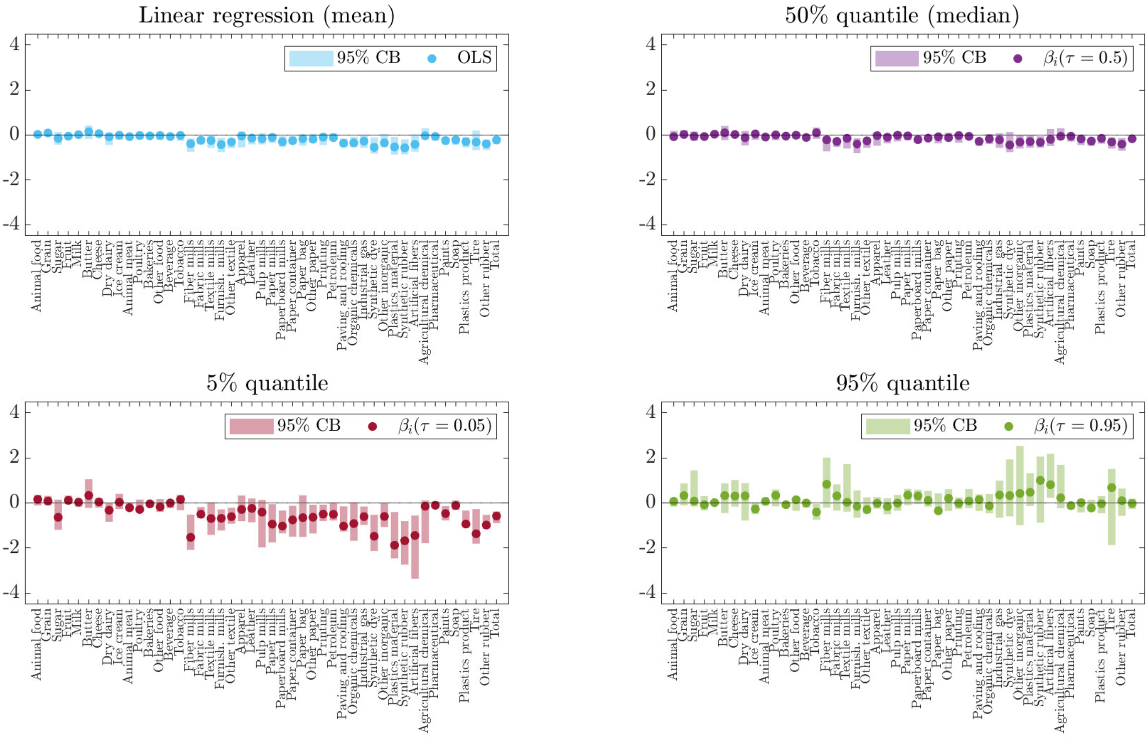


Figure C.4: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for the nondurable goods sector at the six-digit NAICS level (with 95% bootstrap confidence bounds)

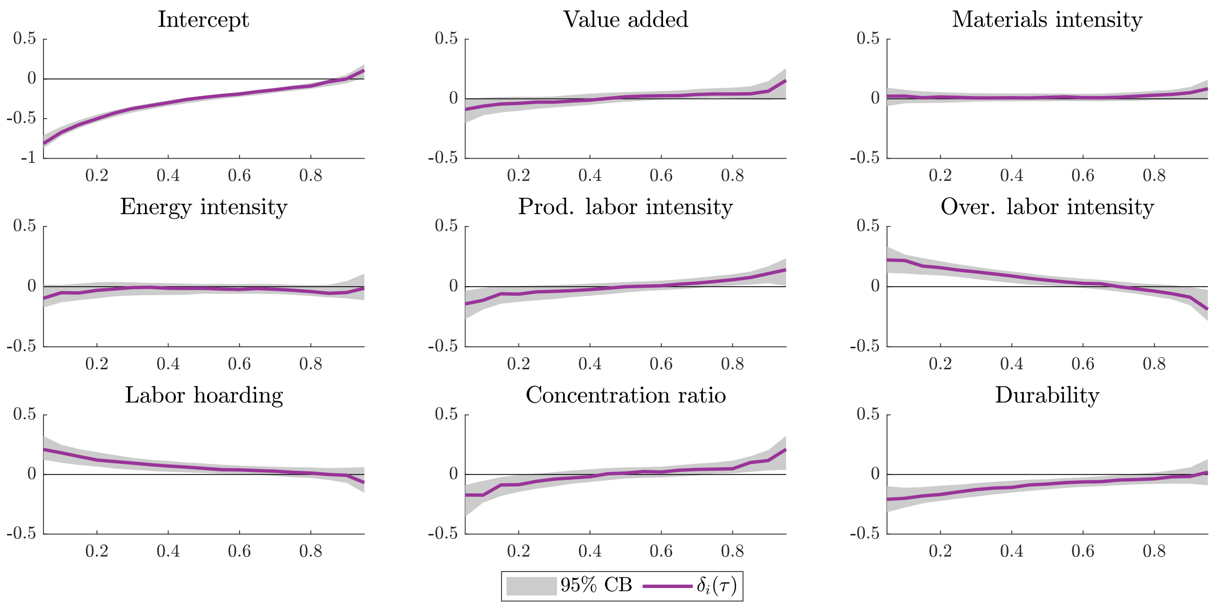


Figure C.5: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the total manufacturing sector at the six-digit NAICS level (with 95% bootstrap confidence bounds)

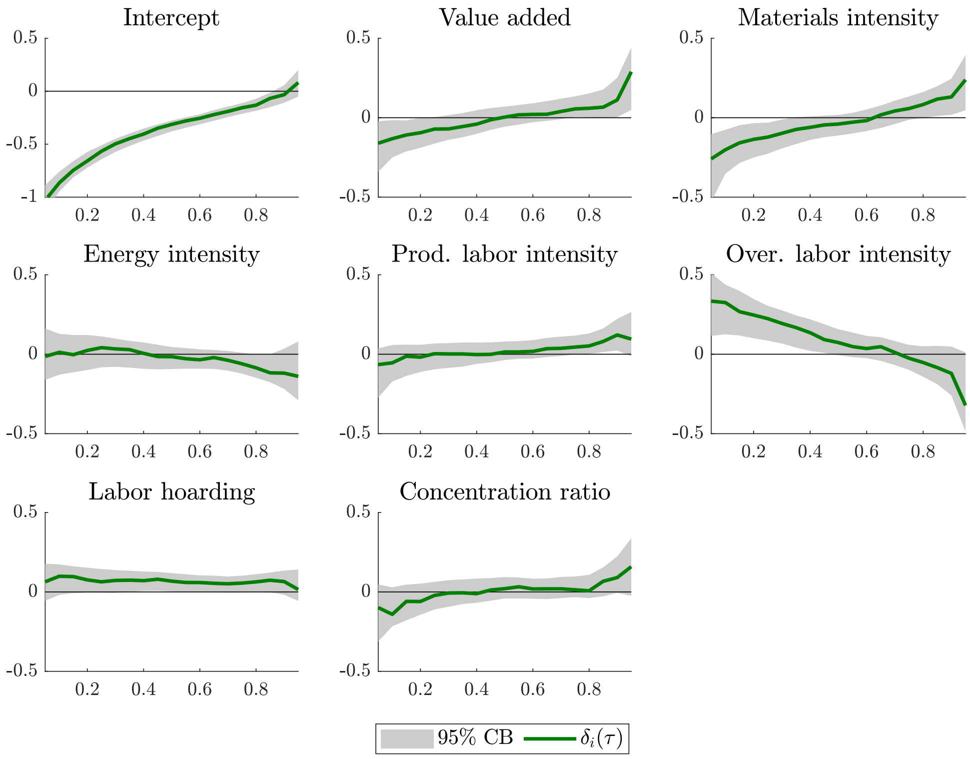


Figure C.6: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the durable goods sector at the six-digit NAICS level (with 95% bootstrap confidence bounds)

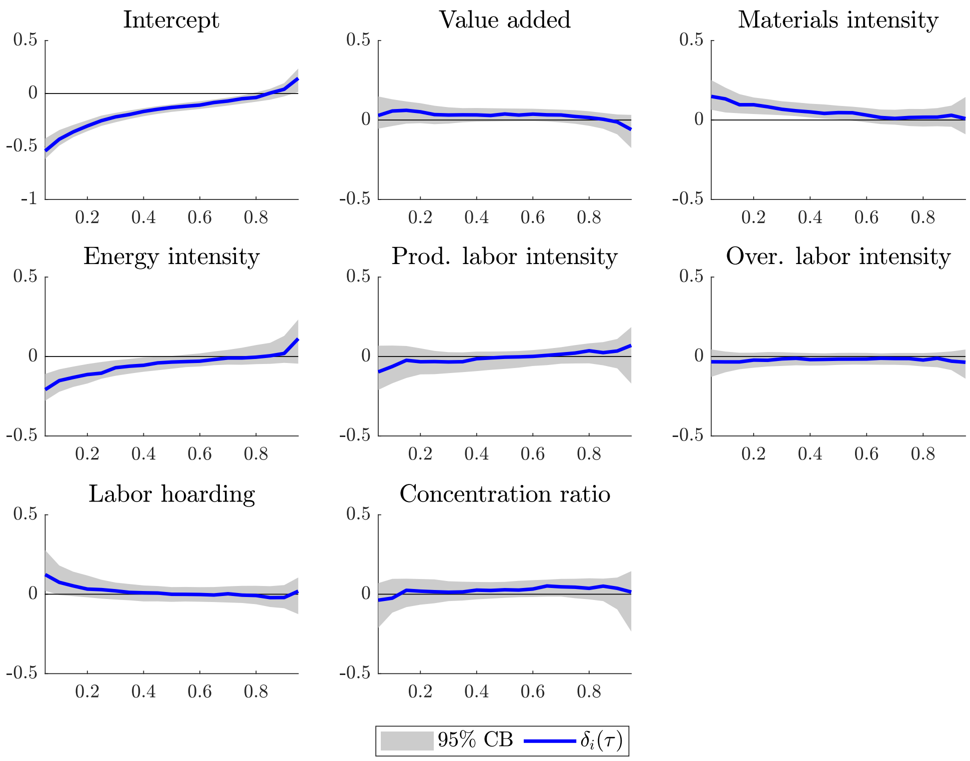


Figure C.7: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the nondurable goods sector at the six-digit NAICS level (with 95% bootstrap confidence bounds)

D Overview of manufacturing industries

Table D.1: Overview of U.S. manufacturing sector industries

Industries	NAICS Code	Selection		
		3-digit	4-digit	6-digit
Food	311	V		
Animal food	3111		V	V
Grain and oilseed milling	3112		V	V
Sugar and confectionery product	3113		V	V
Fruit and vegetable preserving and specialty food	3114		V	V
Dairy product	3115		V	
Fluid milk	311511			V
Creamery butter	311512			V
Cheese	311513			V
Dry, condensed, and evaporated dairy product	311514			V
Ice cream and frozen dessert	31152			V
Animal slaughtering and processing	3116		V	
Animal (except poultry) slaughtering and meat	311611-3			V
Poultry processing	311615			V
Bakeries and tortilla	3118		V	V
Other food	3119		V	V
Beverage and tobacco product	312	V		
Beverage	3121		V	V
Tobacco	3122		V	V
Textile mills	313	V		
Fiber, yarn, and thread mills	3131		V	V
Fabric mills	3132		V	V
Textile and fabric finishing and fabric coating mills	3133		V	V
Textile product mills	314	V		
Textile furnishings mills	3141		V	V
Other textile product mills	3149		V	V
Apparel	315	V	V	V
Leather and allied product	316	V	V	V
Wood product	321	V		
Sawmills and wood preservation	3211		V	V
Veneer, plywood, and engineered wood product	3212		V	V
Other wood product	3219		V	
Millwork	32191			V
Wood container and pallet	32192			V
All other wood product	32199			V
Paper	322	V		
Pulp, paper, and paperboard mills	3221		V	
Pulp mills	32211			V
Paper mills	32212			V

Table D.1: Continued

Industries	NAICS Code	Selection		
		3-digit	4-digit	6-digit
Paperboard mills	32213			V
Converted paper product	3222		V	
Paperboard container	32221			V
Paper bag and coated and treated paper	32222			V
Other converted paper products	32223,9			V
Printing and related support activities	323	V	V	V
Petroleum and coal products	324	V	V	
Petroleum refineries	32411			V
Paving, roofing, and other petroleum and coal	32412,9			V
Chemicals	325	V		
Basic chemical	3251		V	
Organic chemicals	32511,9			V
Industrial gas	32512			V
Synthetic dye and pigment	32513			V
Other basic inorganic chemical	32518			V
Resin, synthetic rubber, and synthetic fibers	3252		V	
Plastics material and resin	325211			V
Synthetic rubber	325212			V
Artificial and synthetic fibers and filaments	32522			V
Pesticide, fertilizer, and other agricultural chemical	3253		V	V
Pharmaceutical and medicine	3254		V	V
Paints and other chemical products	3255,9		V	V
Soap, cleaning compound, and toilet preparation	3256		V	V
Plastics and rubber products	326	V		
Plastics product	3261		V	V
Rubber product	3262		V	
Tire	32621			V
Rubber products ex. tires	32622,9			V
Nonmetallic mineral product	327	V		
Clay product and refractory	3271		V	
Pottery, ceramics, and plumbing fixture	32711			V
Clay building material and refractories	32712			V
Glass and glass product	3272		V	V
Cement and concrete product	3273		V	
Cement	32731			V
Concrete and product	32732-9			V
Lime and gypsum product	3274		V	V
Other nonmetallic mineral product	3279		V	V
Primary metals	331	V		
Iron and steel products	3311,2		V	V
Alumina and aluminum production and processing	3313		V	V
Nonferrous metal (except aluminum) production	3314		V	V

Table D.1: Continued

Industries	NAICS Code	Selection		
		3-digit	4-digit	6-digit
and processing				
Foundries	3315		V	V
Fabricated metal product	332	V		
Forging and stamping	3321		V	V
Cutlery and handtool	3322		V	V
Architectural and structural metals	3323		V	V
Hardware	3325		V	V
Spring and wire product	3326		V	V
Machine shops; turned product; and screw, nut, and bolt	3327		V	V
Coating, engraving, heat treating, and allied activities	3328		V	V
Other fabricated metal product	3329		V	V
Machinery	333	V		
Agriculture, construction, and mining machinery	3331		V	
Agricultural implement	33311			V
Construction machinery	33312			V
Mining and oil and gas field machinery	33313			V
Industrial machinery	3332		V	V
Commercial and service industry machinery and other general purpose machinery	3333,9		V	V
Ventilation, heating, air-conditioning, and commercial refrigeration equipment	3334		V	V
Metalworking machinery	3335		V	V
Engine, turbine, and power transmission equipment	3336		V	V
Computer and electronic product	334	V		
Computer and peripheral equipment	3341		V	V
Communications equipment	3342		V	V
Audio and video equipment	3343		V	V
Semiconductor and other electronic component	3344		V	V
Navigational, measuring, electromedical, and control instruments	3345		V	V
Electrical, equipment, appliance, and component	335	V		
Electric lighting equipment	3351		V	V
Household appliance	3352		V	
Small electrical appliance	33521			V
Major appliance	33522			V
Electrical equipment	3353		V	V
Other electrical equipment and component	3359		V	
Battery	33591			V
Communication and energy wire and cable	33592			V
Other electrical equipment	33593,9			V
Transportation equipment	336	V		
Motor vehicle	3361		V	

Table D.1: Continued

Industries	NAICS Code	Selection		
		3-digit	4-digit	6-digit
Automobile	336111			V
Light truck and utility vehicle	336112			V
Heavy duty truck	33612			V
Motor vehicle body and trailer	3362		V	V
Motor vehicle parts	3363		V	V
Aerospace product and parts	3364		V	V
Railroad rolling stock	3365		V	V
Ship and boat building	3366		V	V
Other transportation equipment	3369		V	V
Furniture and related product	337	V		
Household and institutional furniture and kitchen cabinet	3371		V	V
Office and other furniture	3372,9		V	V
Miscellaneous	339	V	V	V
Total manufacturing sector	31-33			

E Additional industry characteristics analysis

E.1 Time variation of industry characteristics

Figure E.1 shows the annual industry characteristics over time for industries at the three-digit NAICS level. Although the characteristics display some time variation, the ranking of the characteristics across industries over time seems to be rather constant. Also, there does not seem to be a structural breaks for any of the characteristics, except that the production labor intensities shows a distinct downward sloping trend for all industries. Overall, based on Figure E.1, it seems justified to average the industry characteristics over time.

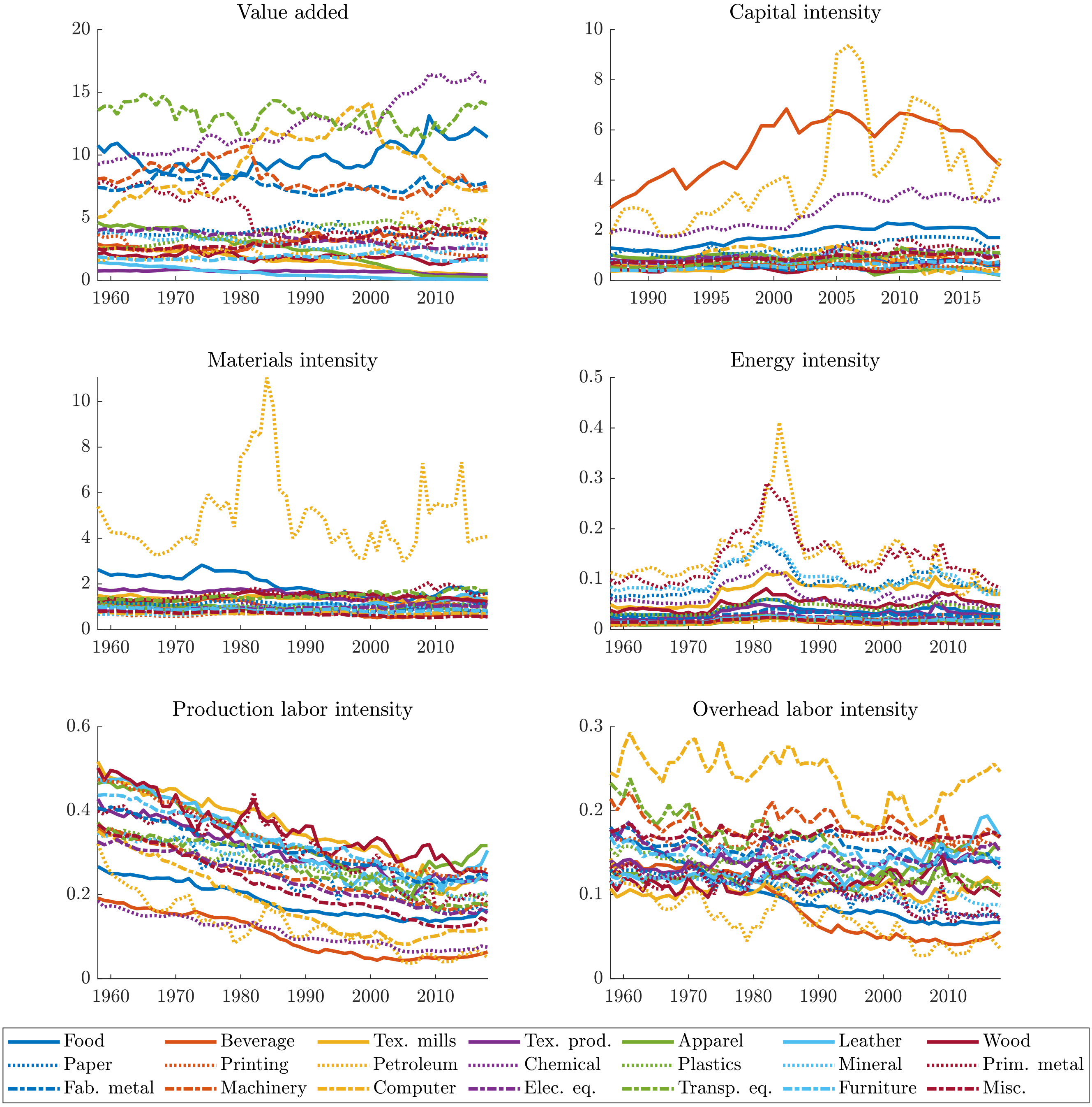


Figure E.1: Time series of annual characteristics of industries at the three-digit NAICS level

E.2 Robustness to starting dates of industry characteristics

Figures E.2, E.3 and E.4 show the industry-characteristic effects for three different starting dates of the characteristics constructed with the NBER-CES manufacturing database (that is, value added, capital intensity, material intensity, energy intensity, production and overhead labor intensities, and labor hoarding). More specifically, the starting dates are 1958, 1973 (start of NFCI and IP data) and 1987 (start of BLS-MFP data).

For the total manufacturing sector in Figure E.2, we generally find that most industry-characteristic effects are robust to the start date, except for the production labor intensity, the labor hoarding measure and the durability dummy. The latter is thus influenced by the change in starting date of the other characteristics as the classification of durable goods industries remained the same over the three different samples. Next, for the durable goods sector in Figure E.3, there are some small differences in the effects for the overhead labor intensity and labor hoarding measures, while the other effects are robust. Lastly, for the nondurable goods sector in Figure E.4, there seem to be more deviations in the effects across subsample, albeit that these effects are often not significant for the baseline sample 1958 to 2018 (see Figure 8 in the main text). A more complete subsample analysis from 1973 onwards of the industry-characteristic effects can be found in the results section in the main text.

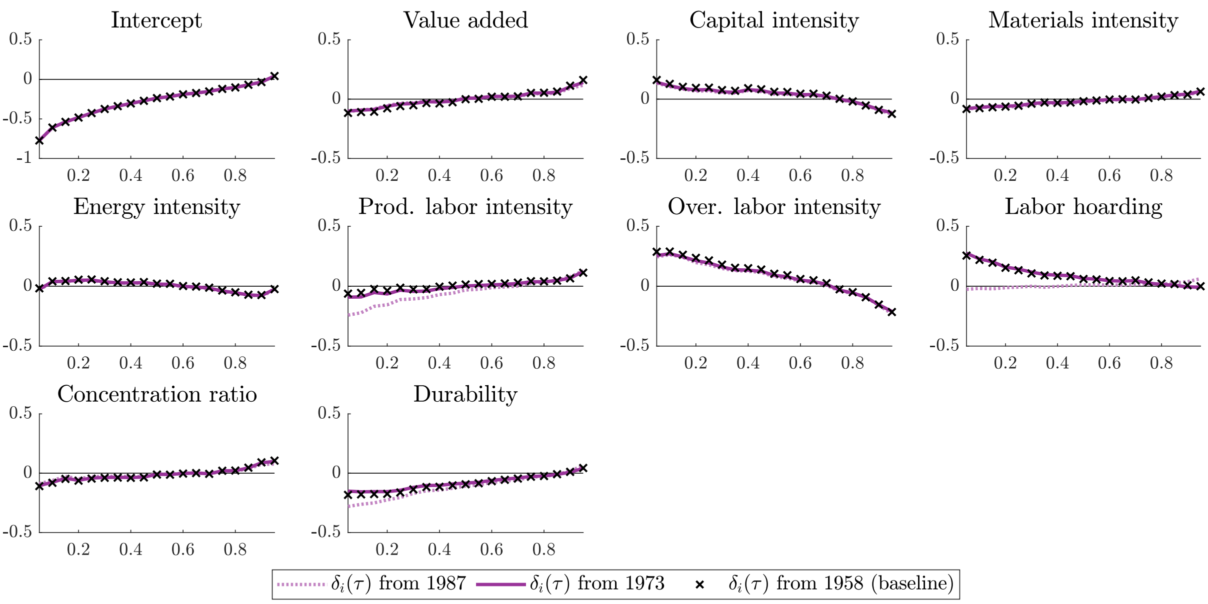


Figure E.2: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the total manufacturing sector for different starting periods of the average industry characteristics

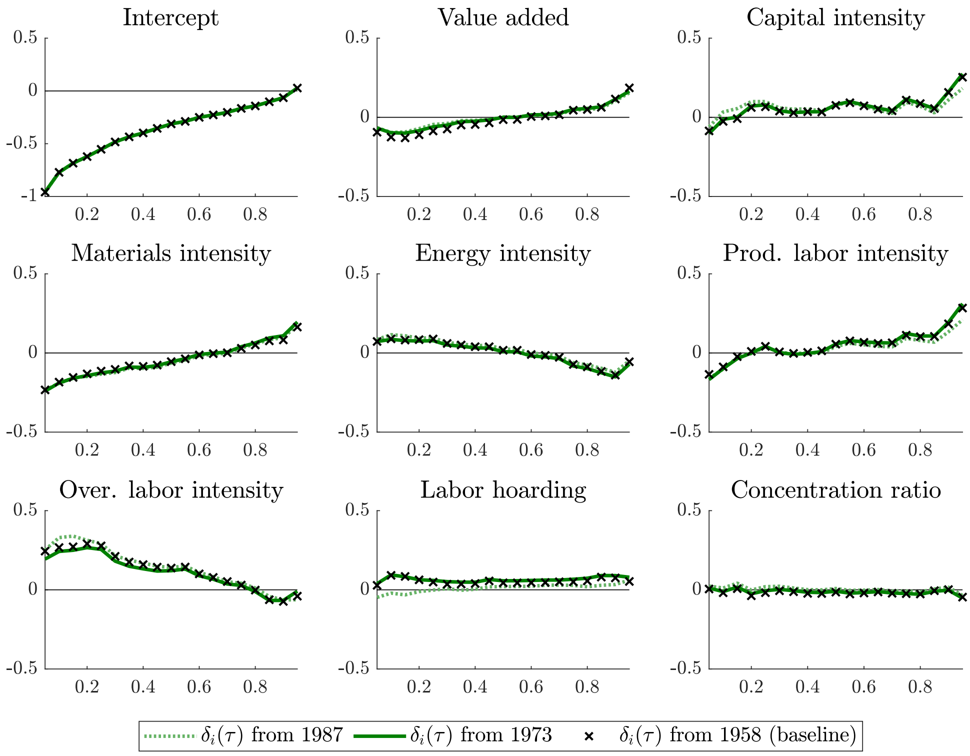


Figure E.3: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the durable goods sector for different starting periods of the average industry characteristics

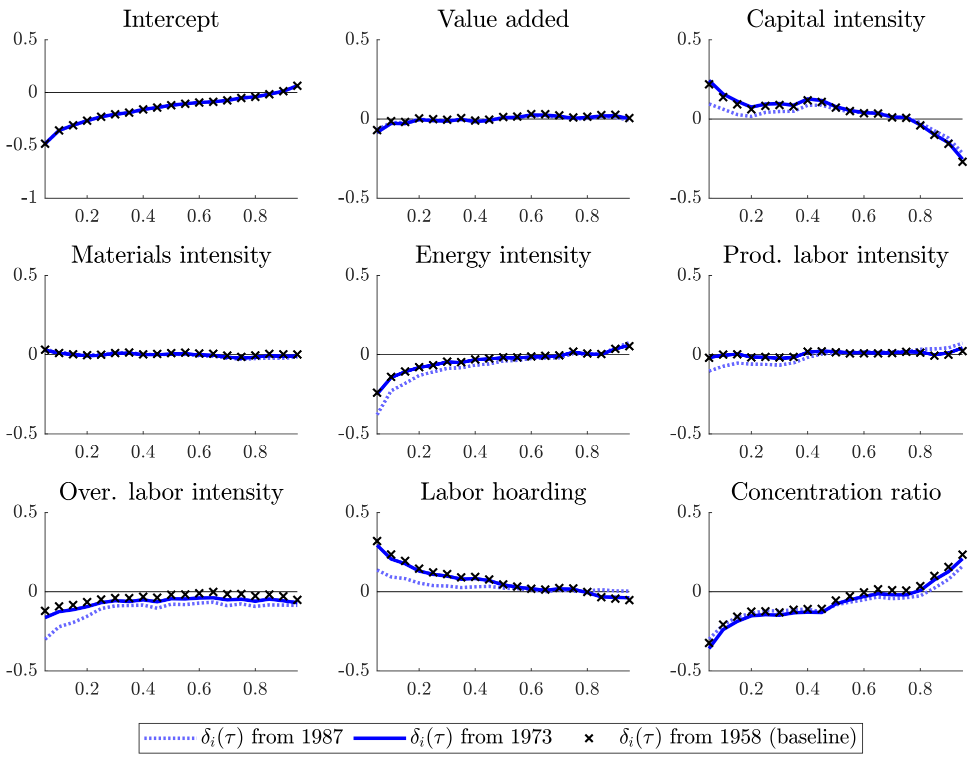


Figure E.4: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the nondurable goods sector for different starting periods of the average industry characteristics

E.3 Cross-correlations of industry characteristics

Table E.1 shows the cross-correlations and variance inflation factors (VIF) of the industry characteristics for the three levels of disaggregation. For the four-digit and six-digit NAICS levels, these correlations and VIFs are quite low. Hence, multi-collinearity is not an issue here. For the three-digit NAICS level, however, we find high VIFs for the capital intensity, production labor intensity and labor hoarding measure. Therefore, we remove the capital intensity in the regression of the three-digit NAICS level, which brings down the VIFs to a sufficient level.

Table E.1: Correlation matrix and VIFs of industry characteristics

				Correlations						VIF
Panel A: Three-digit NAICS (21 industries)										
	VA	Cap.	Mat.	Energy	ProdL	OverL	LH	CR	Dur.	
VA	1.00									1.92
Cap.	0.07	1.00								18.54
Mat.	-0.07	**0.48**	1.00							2.45
Energy	-0.12	0.27	**0.58**	1.00						3.23
ProdL	**-0.45**	**-0.81**	-0.30	-0.12	1.00					7.66
OverL	0.28	**-0.55**	**-0.50**	**-0.62**	0.17	1.00				4.55
LH	-0.04	**0.90**	**0.51**	0.11	**-0.68**	**-0.50**	1.00			9.10
CR	-0.03	**0.73**	**0.46**	0.25	**-0.49**	-0.41	**0.66**	1.00		2.60
Dur.	0.23	-0.39	-0.27	-0.11	0.18	**0.53**	**-0.50**	-0.36	1.00	1.91
Panel B: Four-digit NAICS (74 industries)										
	VA	Cap.	Mat.	Energy	ProdL	OverL	LH	CR	Dur.	
VA	1.00									1.24
Cap.	0.09	1.00								2.49
Mat.	-0.01	0.11	1.00							1.36
Energy	-0.12	0.02	**0.25**	1.00						1.38
ProdL	**-0.30**	**-0.58**	-0.11	0.02	1.00					2.49
OverL	0.22	**-0.47**	**-0.38**	**-0.45**	0.13	1.00				2.53
LH	0.16	**0.51**	**0.31**	0.02	**-0.66**	**-0.31**	1.00			2.64
CR	-0.01	**0.57**	**0.25**	0.09	**-0.44**	**-0.34**	**0.36**	1.00		1.72
Dur.	-0.13	**-0.38**	**-0.27**	-0.08	**0.37**	**0.46**	**-0.60**	-0.13	1.00	1.98
Panel C: Six-digit NAICS (101 industries)										
	VA	Mat.	Energy	ProdL	OverL	LH	CR	Dur.		
VA	1.00									1.25
Mat.	-0.13	1.00								1.27
Energy	**-0.22**	0.05	1.00							1.27
ProdL	-0.18	-0.08	-0.15	1.00						1.99
OverL	**0.33**	**-0.32**	**-0.43**	0.17	1.00					1.89
LH	0.07	**0.26**	**0.20**	**-0.62**	**-0.34**	1.00				2.19
CR	-0.18	**0.35**	0.18	**-0.40**	**-0.45**	**0.32**	1.00			1.62
Dur.	0.01	**-0.25**	-0.18	**0.41**	**0.43**	**-0.59**	**-0.23**	1.00		1.73

Notes: This table shows the correlations and variance inflation factors (VIF) of the industry characteristics at the three-digit, four-digit and six-digit NAICS levels. The VIFs are computed as the diagonal of the inverse of the correlation matrix (see e.g. Mansfield and Helms, 1982). A bold correlation coefficient indicates significance at the 5% level.

F Alternative horizons

F.1 Six months ahead ($h = 6$)

Figures F.1 and F.2 display the quantile and linear regression coefficients of the effect of the NFCI on six-month ahead IP growth ($h = 6$). The figures indicate that these effects are rather similar as for $h = 3$, albeit that they are generally slightly less strong for a longer horizon. Figures F.3, F.4 and, F.5 show the corresponding industry-characteristic effects. Again, we find qualitatively similar effects for $h = 6$ as for $h = 3$, although some effects are less strong for $h = 6$ and therefore not significant anymore.

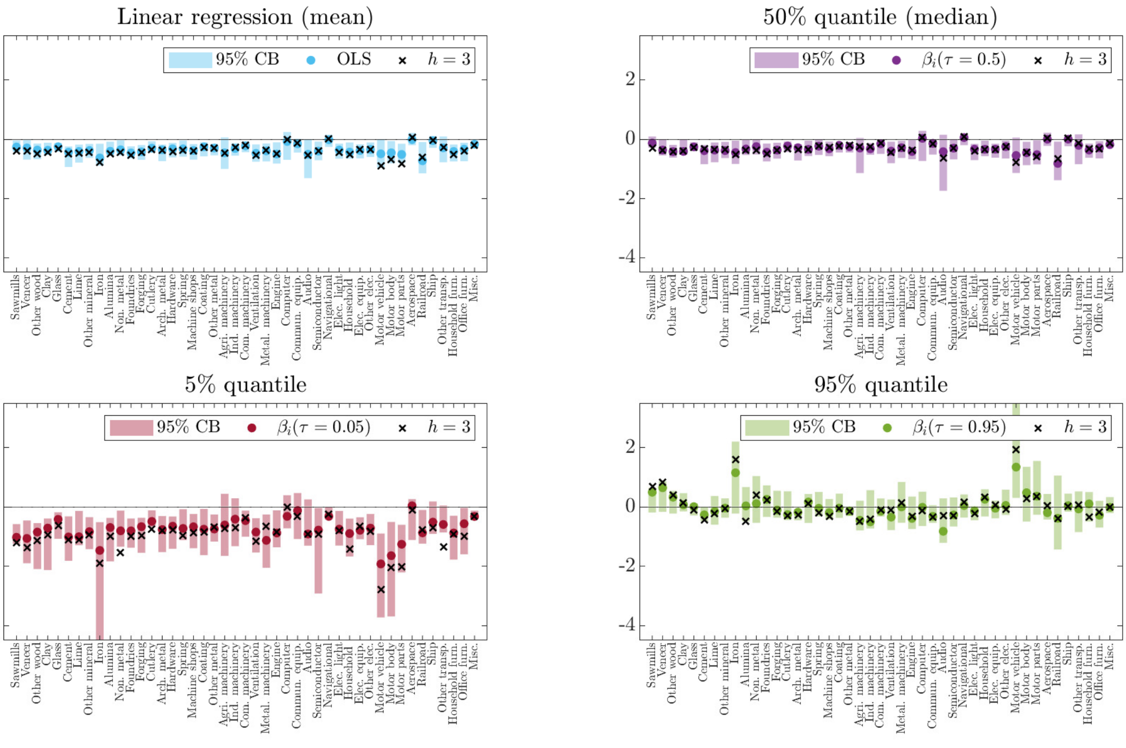


Figure F.1: Estimated linear and quantile regression coefficients of the effect of the NFCI on six-month ahead IP growth ($h = 6$) for the durable goods sector (with 95% bootstrap confidence bands)

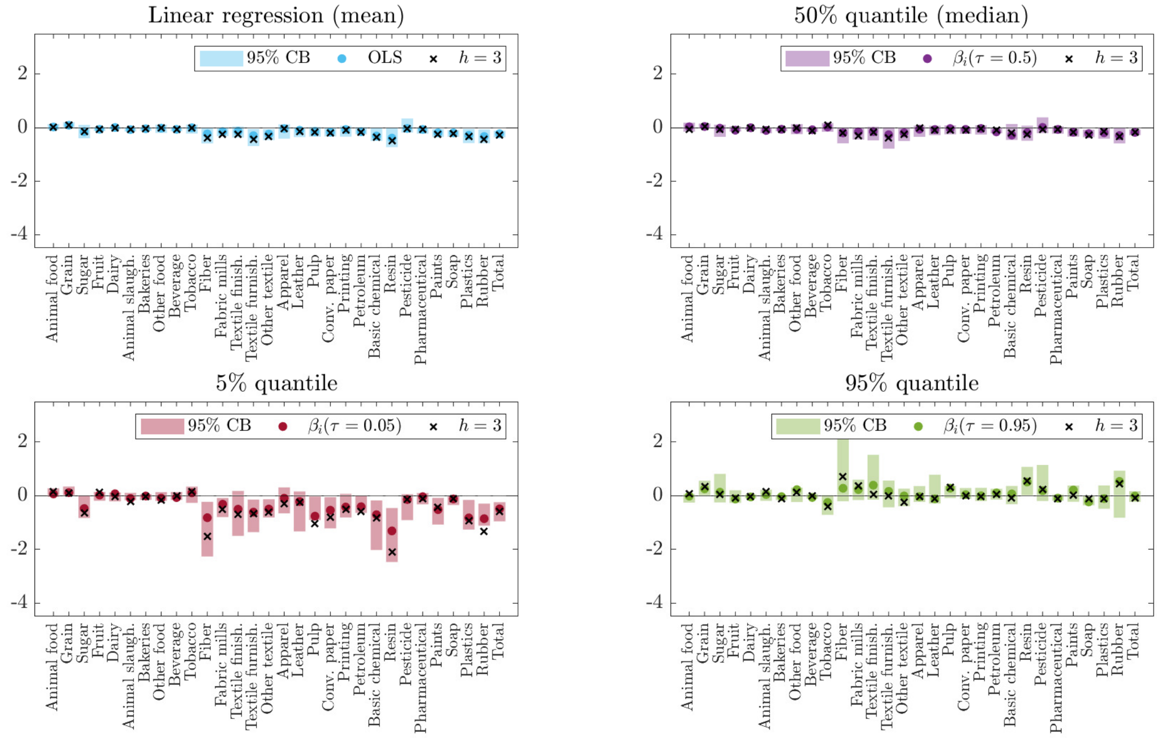


Figure F.2: Estimated linear and quantile regression coefficients of the effect of the NFCI on six-month ahead IP growth ($h = 6$) for the nondurable goods sector (with 95% bootstrap confidence bands)

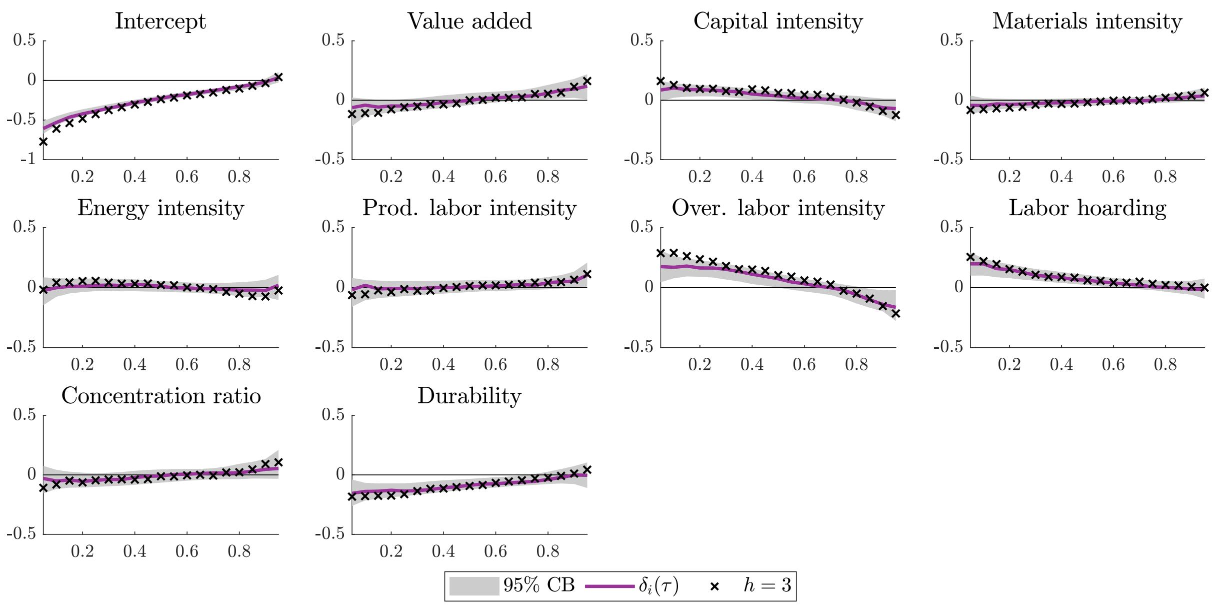


Figure F.3: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 6$ across quantiles for the total manufacturing sector (with 95% bootstrap confidence bands)

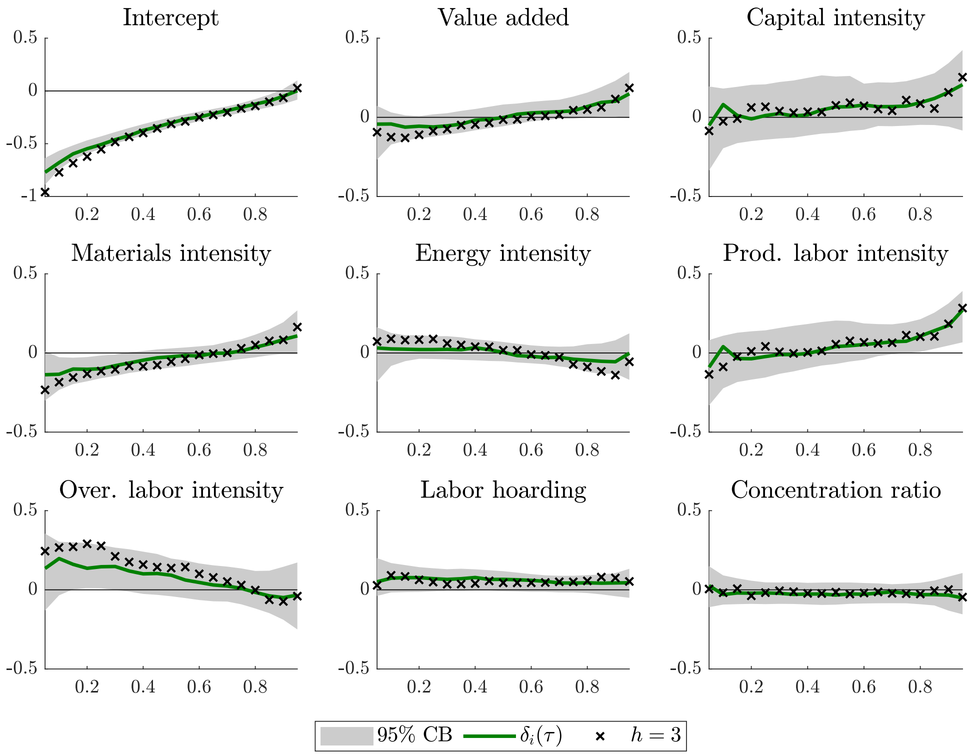


Figure F.4: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 6$ across quantiles for the durable goods sector (with 95% bootstrap confidence bands))

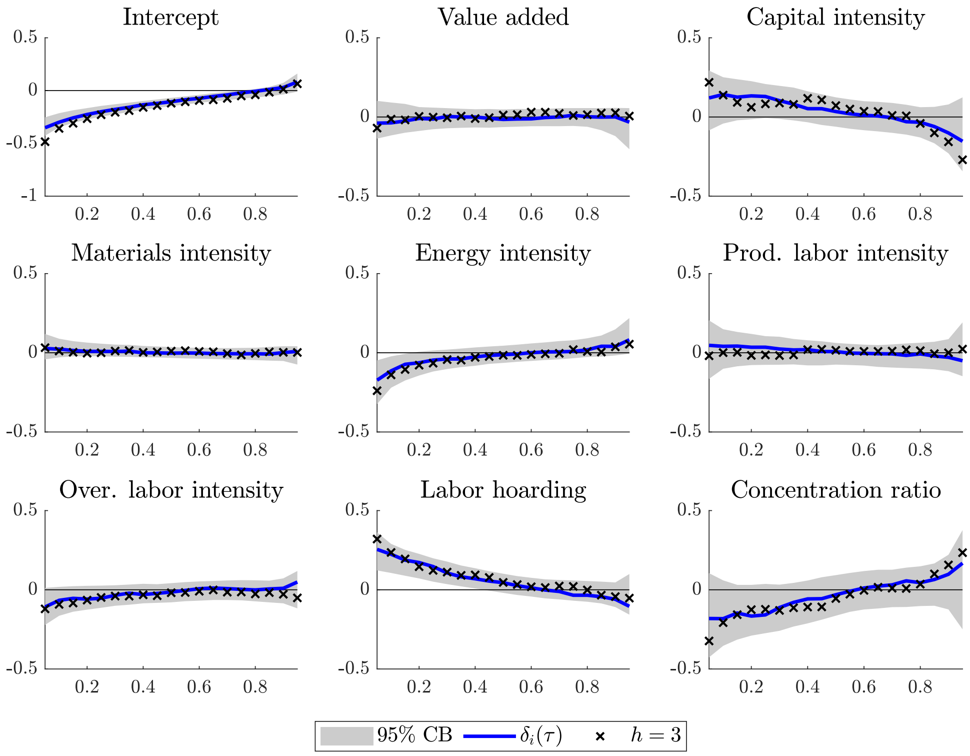


Figure F.5: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 6$ across quantiles for the nondurable goods sector (with 95% bootstrap confidence bands)

F.2 One year ahead ($h = 12$)

Figures F.6 and F.7 show the quantile and linear regression coefficients of the effect of the NFCI on one-year ahead IP growth ($h = 12$). We observe somewhat weaker effects for $h = 12$ as for $h = 3$ for most industries, where they are generally still significant for industries in the durable goods sector but less so for industries in the nondurable goods sector. Figures F.8, F.9 and F.10 show the industry-characteristic effects for $h = 12$. Again, these effects are less strong for $h = 12$ as for $h = 3$, although their slopes are rather similar. Still, due to the weaker effects, most of them are insignificant now, except for the durability dummy in the total manufacturing sector, and the labor hoarding measure in the nondurable goods and total manufacturing sector.

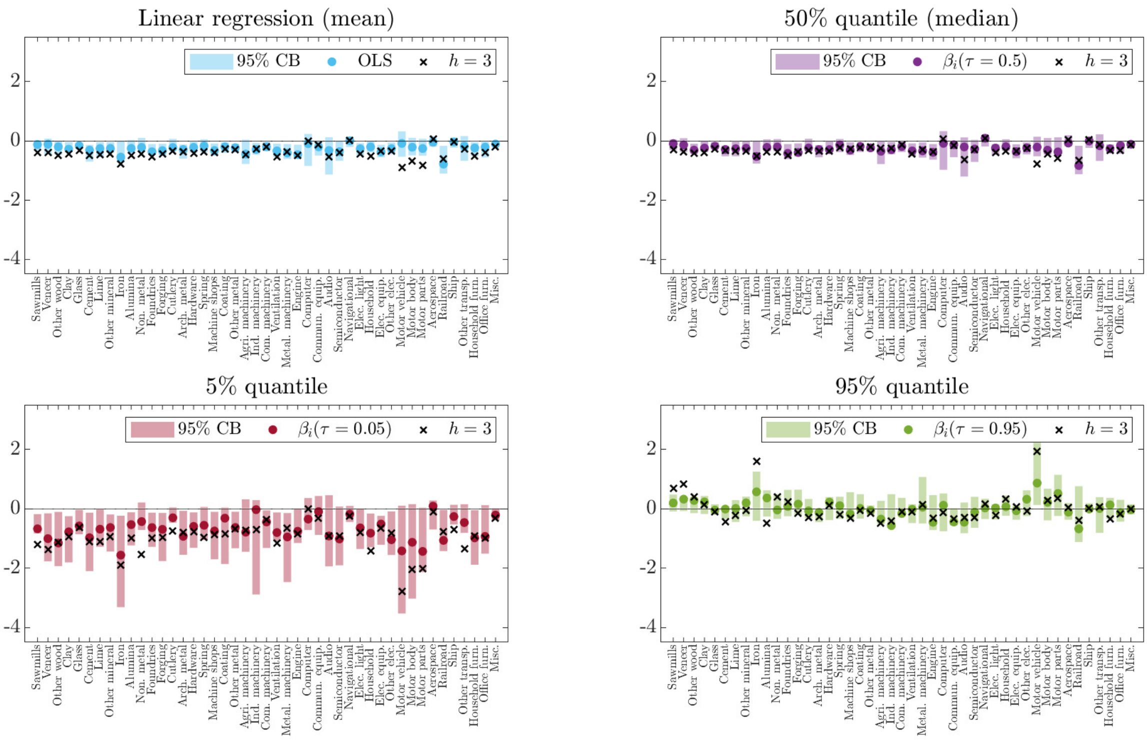


Figure F.6: Estimated linear and quantile regression coefficients of the effect of the NFCI on one year IP growth ($h = 12$) for the durable goods sector (with 95% bootstrap confidence bands)

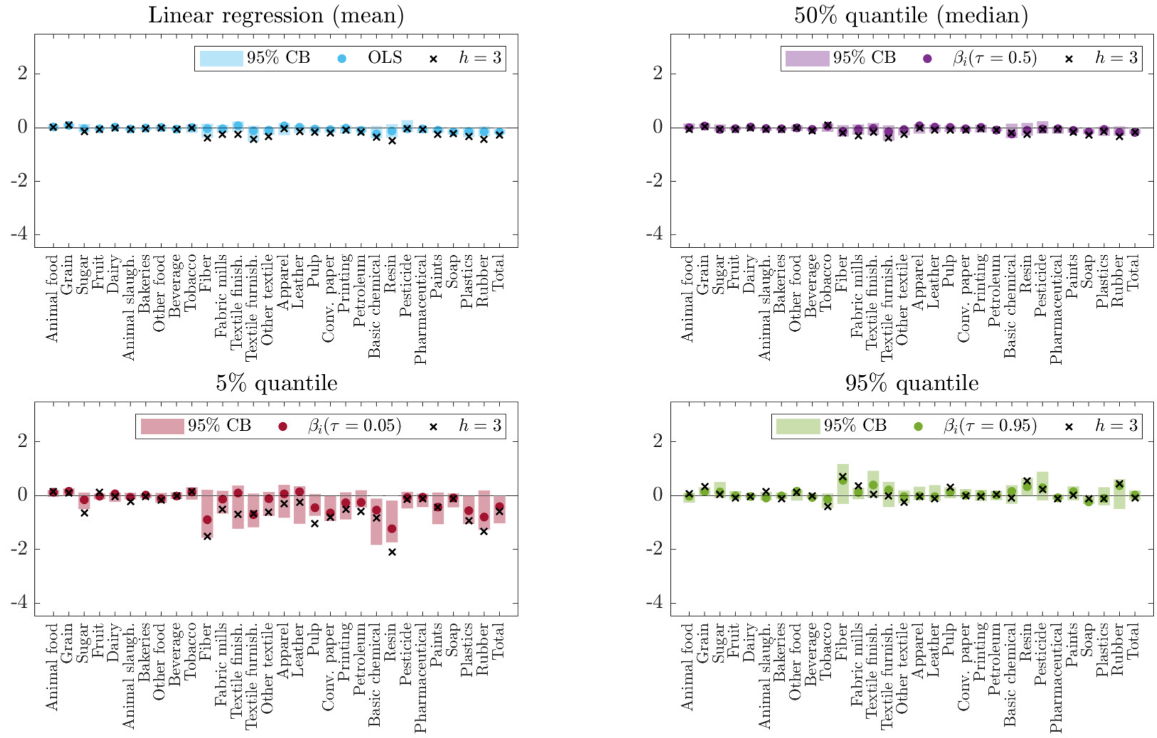


Figure F.7: Estimated linear and quantile regression coefficients of the effect of the NFCI on one year IP growth ($h = 12$) for the nondurable goods sector (with 95% bootstrap confidence bands)

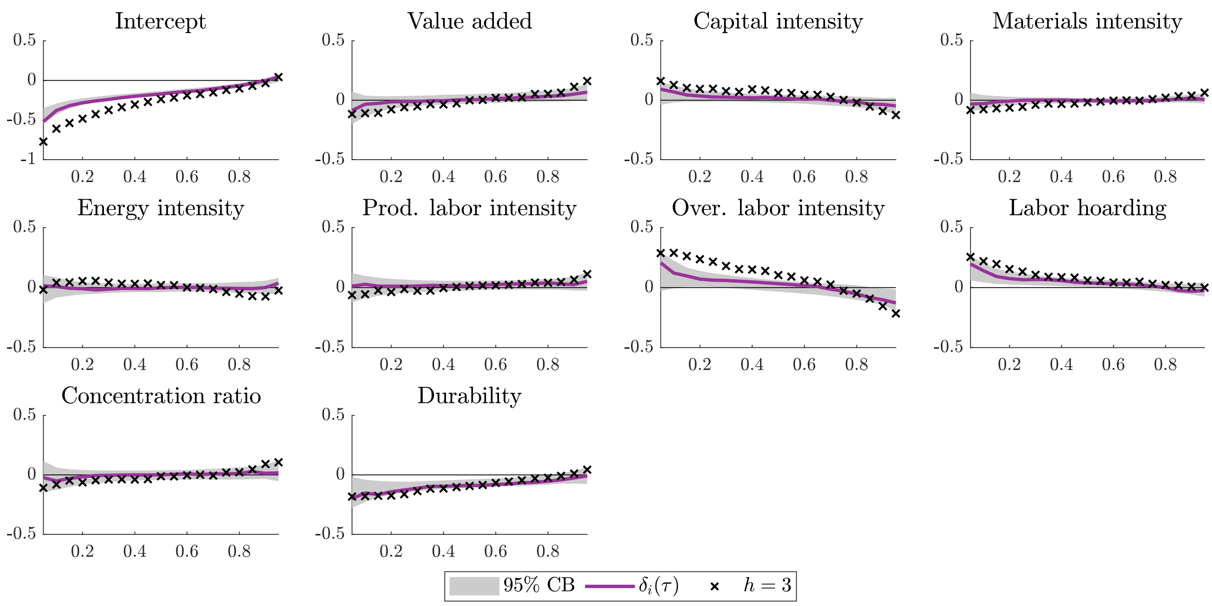


Figure F.8: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 12$ across quantiles for the total manufacturing sector (with 95% bootstrap confidence bands)

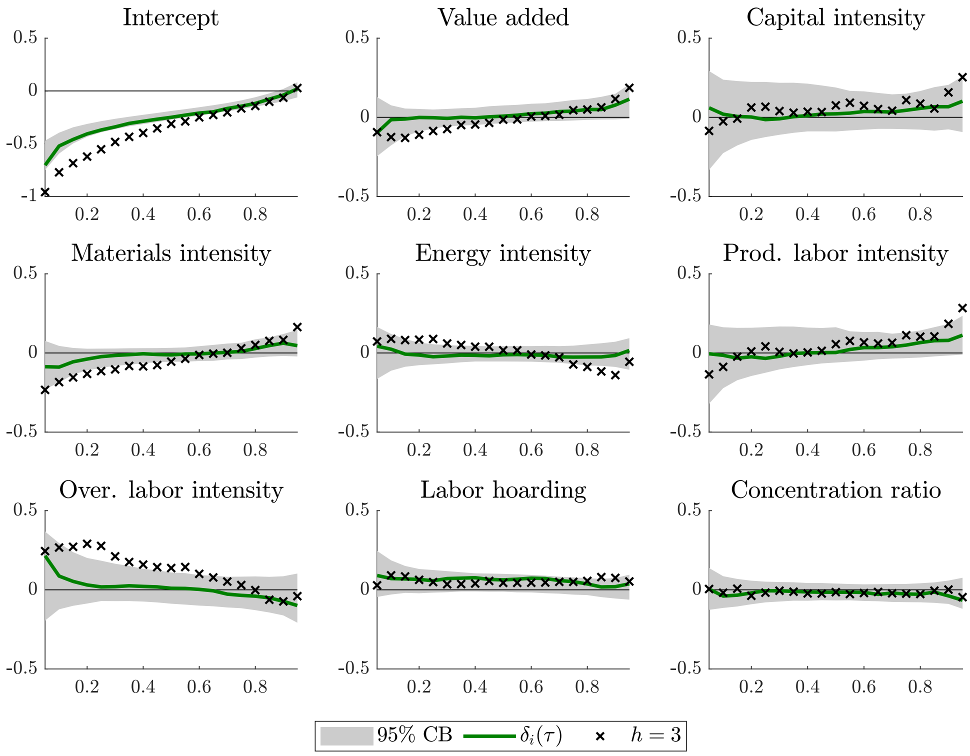


Figure F.9: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 12$ across quantiles for the durable goods sector (with 95% bootstrap confidence bands)

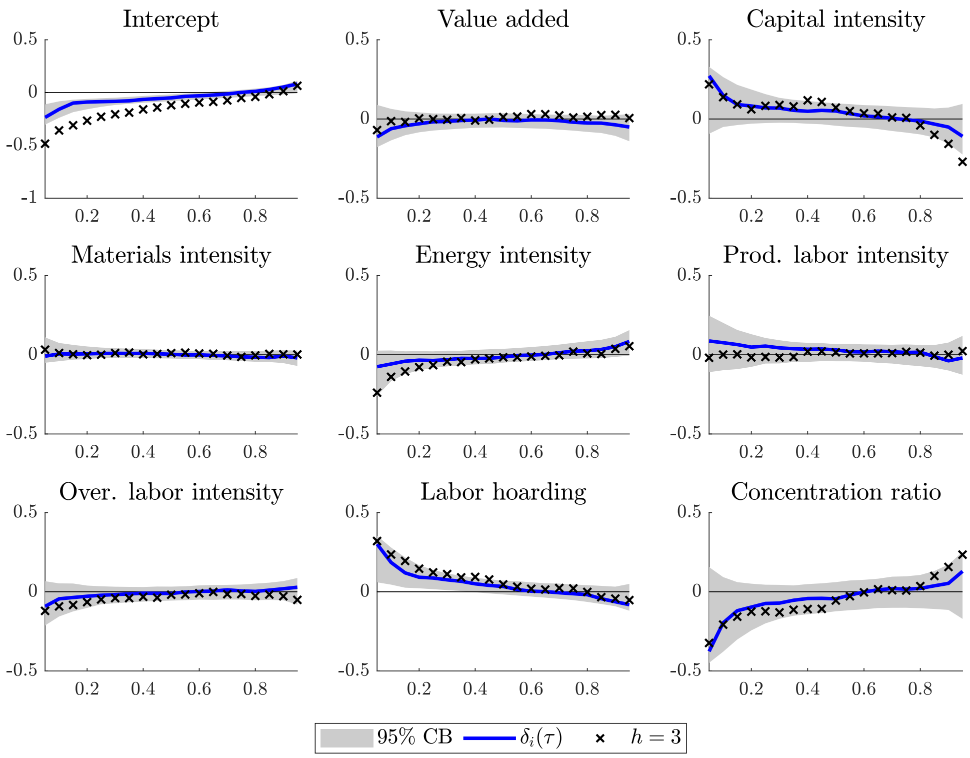


Figure F.10: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 12$ across quantiles for the nondurable goods sector (with 95% bootstrap confidence bands)

G Results of current IP growth

Figures G.1 and G.2 show the estimated linear and quantile regression coefficients of the effect of current IP growth on three-month ahead IP growth ($\hat{\phi}(\tau)$). We find substantial heterogeneity across industries in the coefficients, where the coefficients are generally larger, in absolute terms, for the industries in the durable goods sector than for the industries in the nondurable goods sector. On the other hand, the coefficients at the industry-level do not display much variation between the 5% and 50% quantiles, implying a more linear relation between current IP growth and three-month ahead IP growth. Next, Figures G.3, G.4 and G.5 show the industry-characteristic effects on the current IP coefficients, which all seem to be rather flat. This confirms the more linear relationship between current IP growth and three-month ahead IP growth.

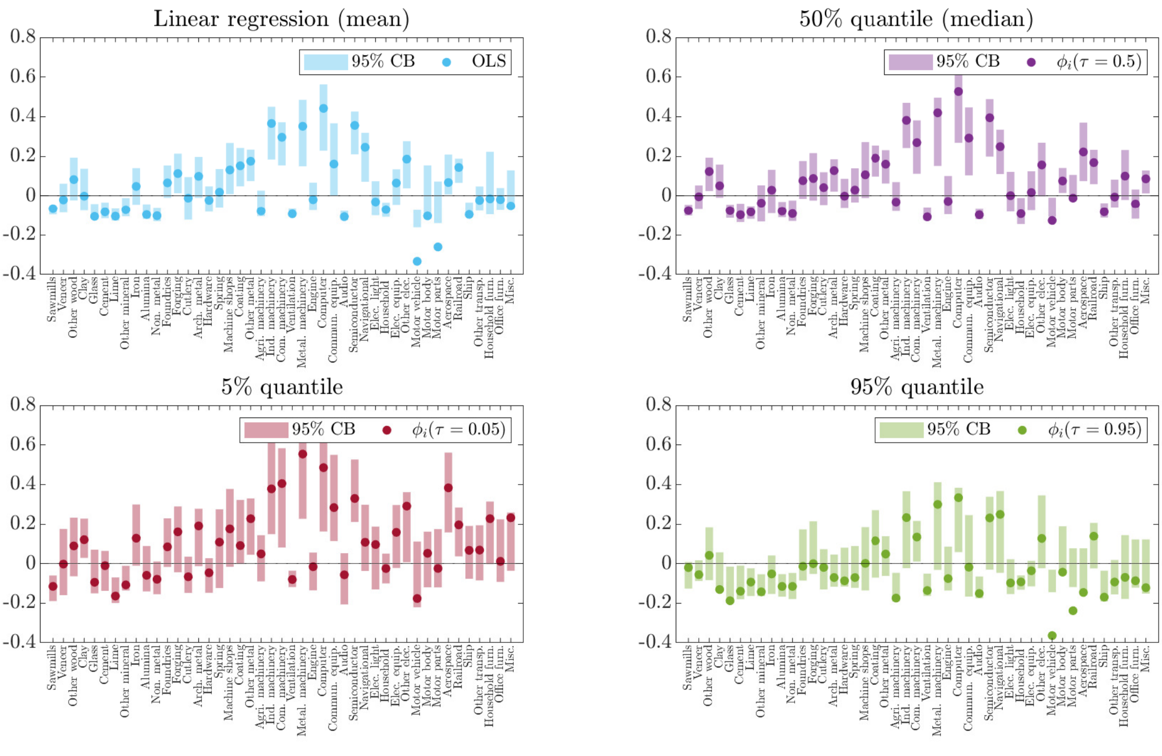


Figure G.1: Estimated linear and quantile regression coefficients of the effect of current IP growth on three-month ahead IP growth ($h = 3$) for the durable goods sector (with 95% bootstrap confidence bands)

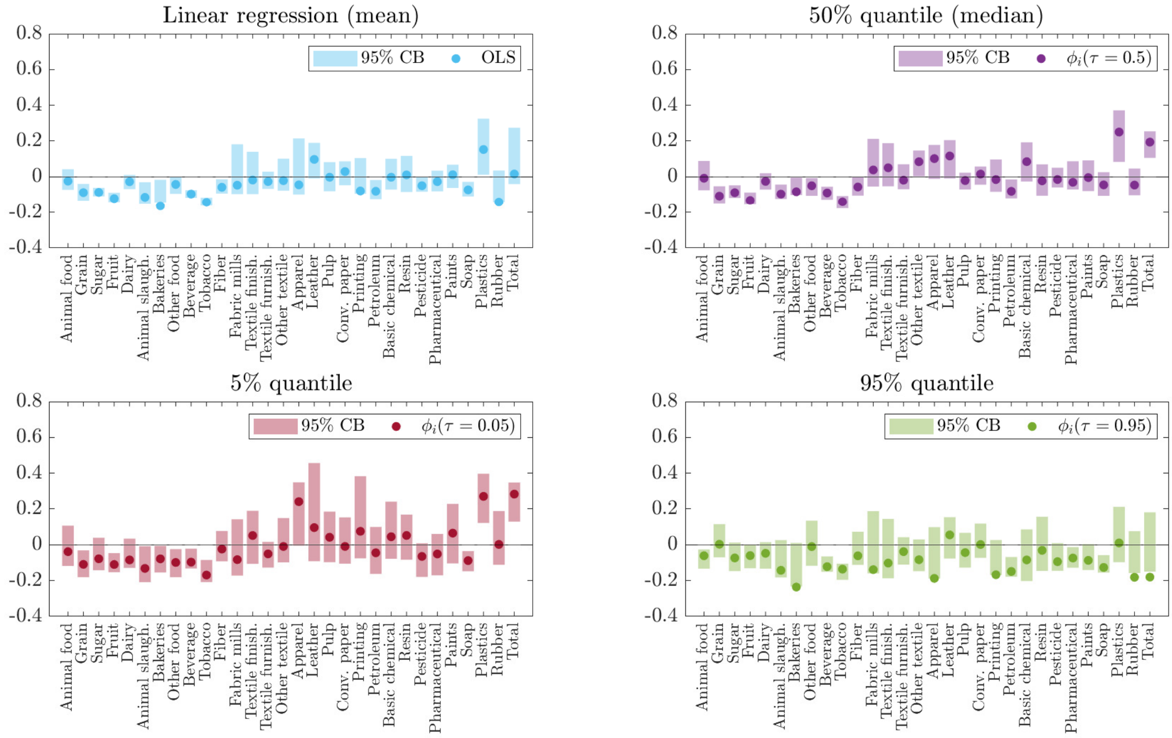


Figure G.2: Estimated linear and quantile regression coefficients of the effect of current IP growth on three-month ahead IP growth ($h = 3$) for the nondurable goods sector (with 95% bootstrap confidence bands)

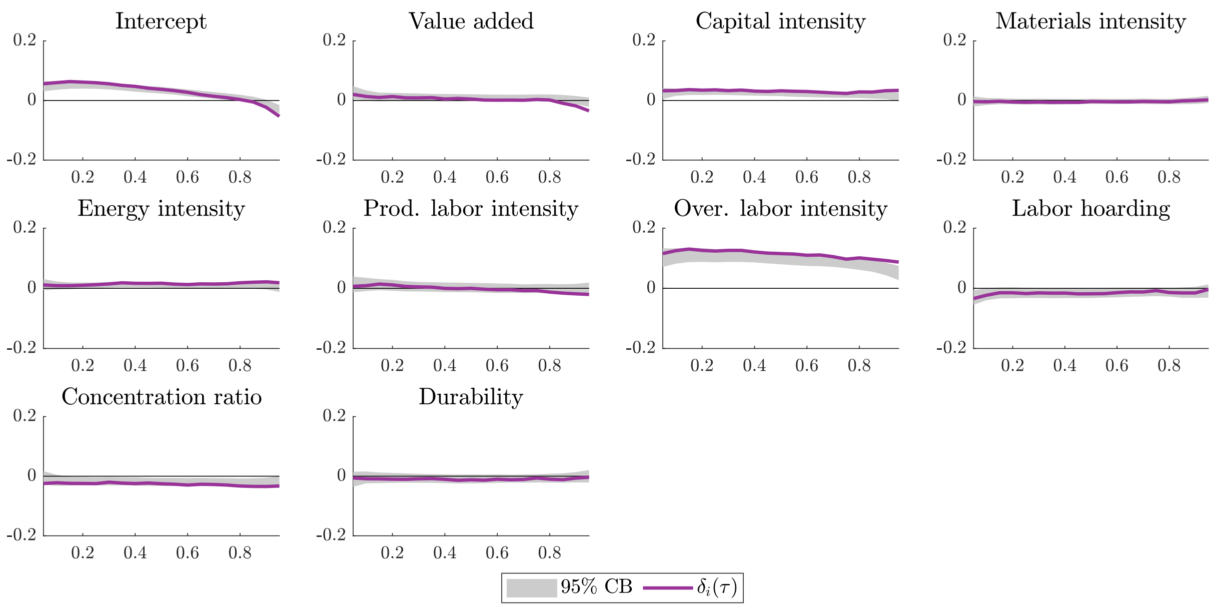


Figure G.3: Estimated industry-characteristic effects on current IP growth quantile coefficients based on $h = 3$ across quantiles for the total manufacturing sector (with 95% bootstrap confidence bands)

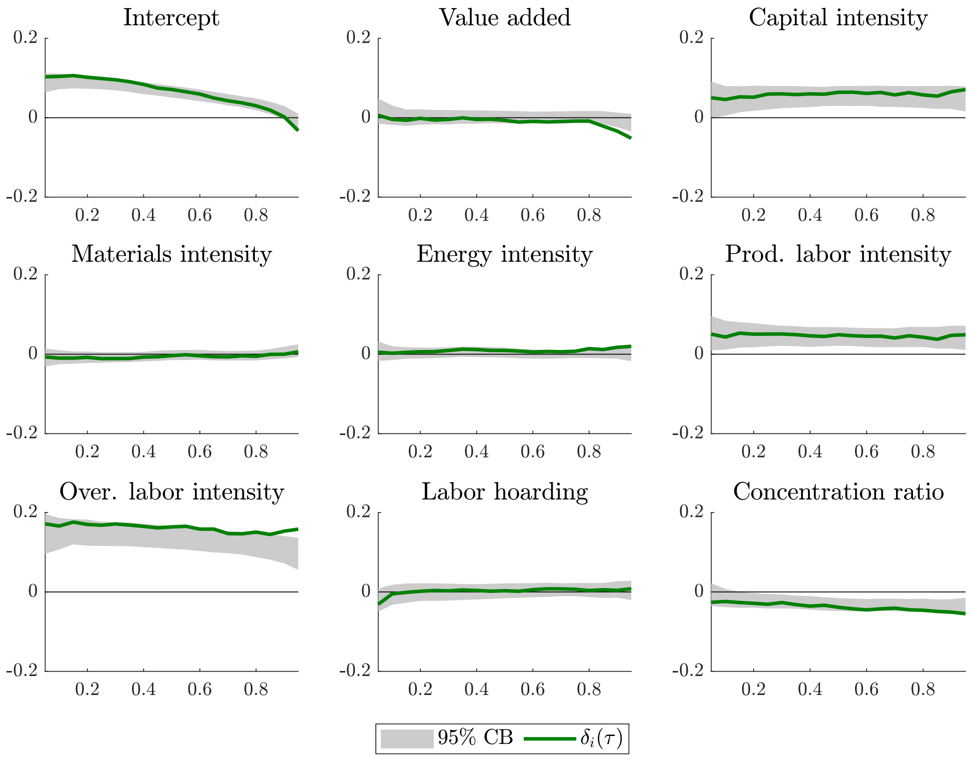


Figure G.4: Estimated industry-characteristic effects on current IP growth quantile coefficients based on $h = 3$ across quantiles for the durable goods sector (with 95% bootstrap confidence bands)

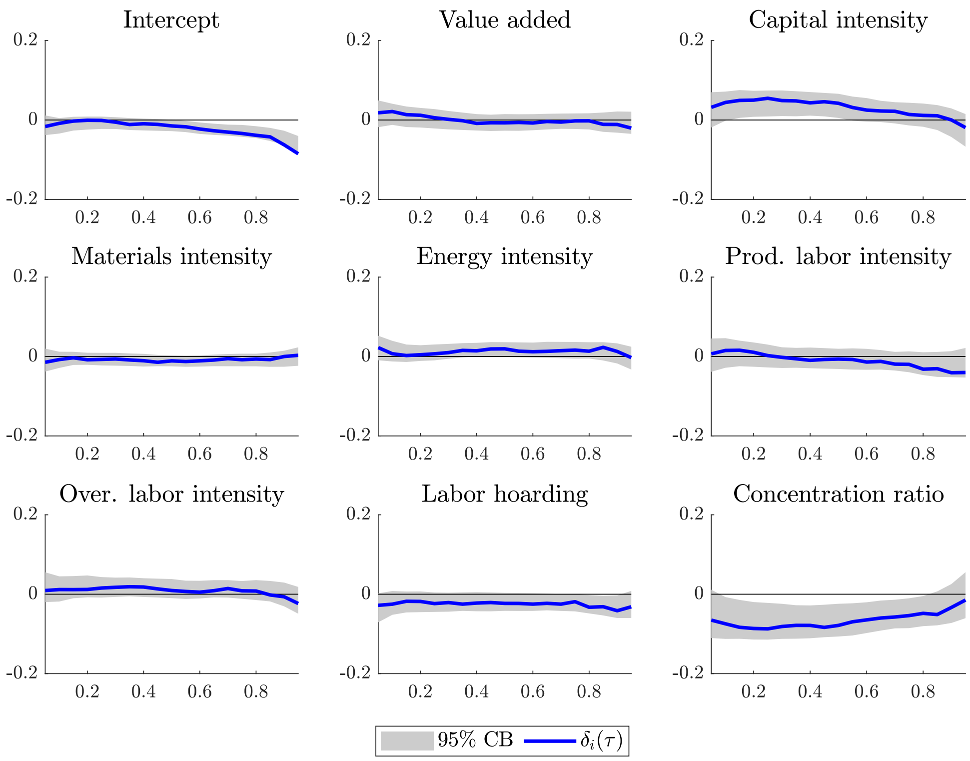


Figure G.5: Estimated industry-characteristic effects on current IP growth quantile coefficients based on $h = 3$ across quantiles for the nondurable goods sector (with 95% bootstrap confidence bands)

H Additional NFCI coefficients across quantiles

Figures H.1 and H.2 show the NFCI quantile regression coefficients across quantiles for the other industries not included in Figure 4 in the main text. Yet, we can draw exactly the same conclusions for these industries as for the ones included in the main text.

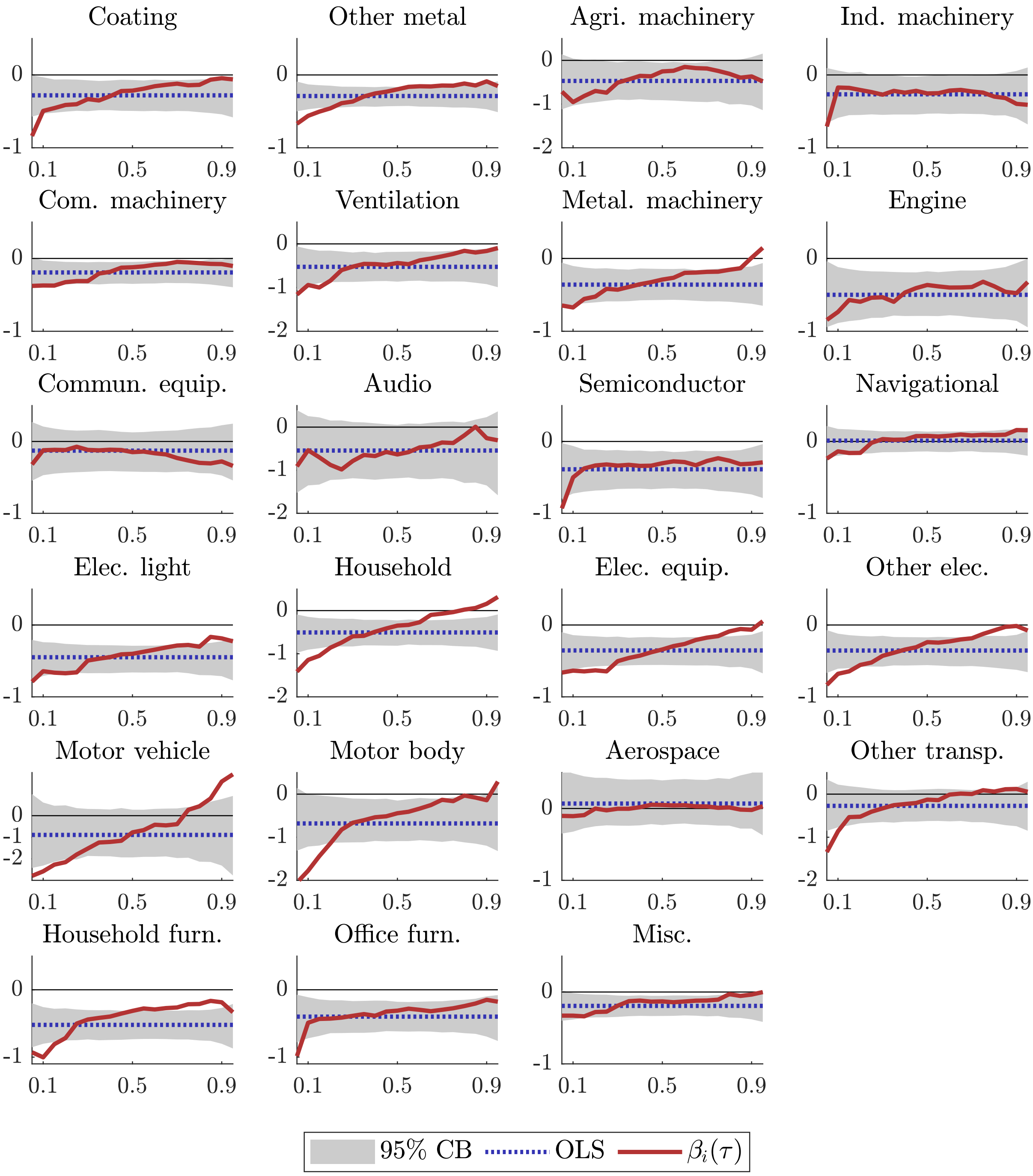


Figure H.1: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) across quantiles (with 95% bootstrap confidence bounds (CB) based on a VAR(4) model for IP and NFCI as data-generating process) for 23 industries

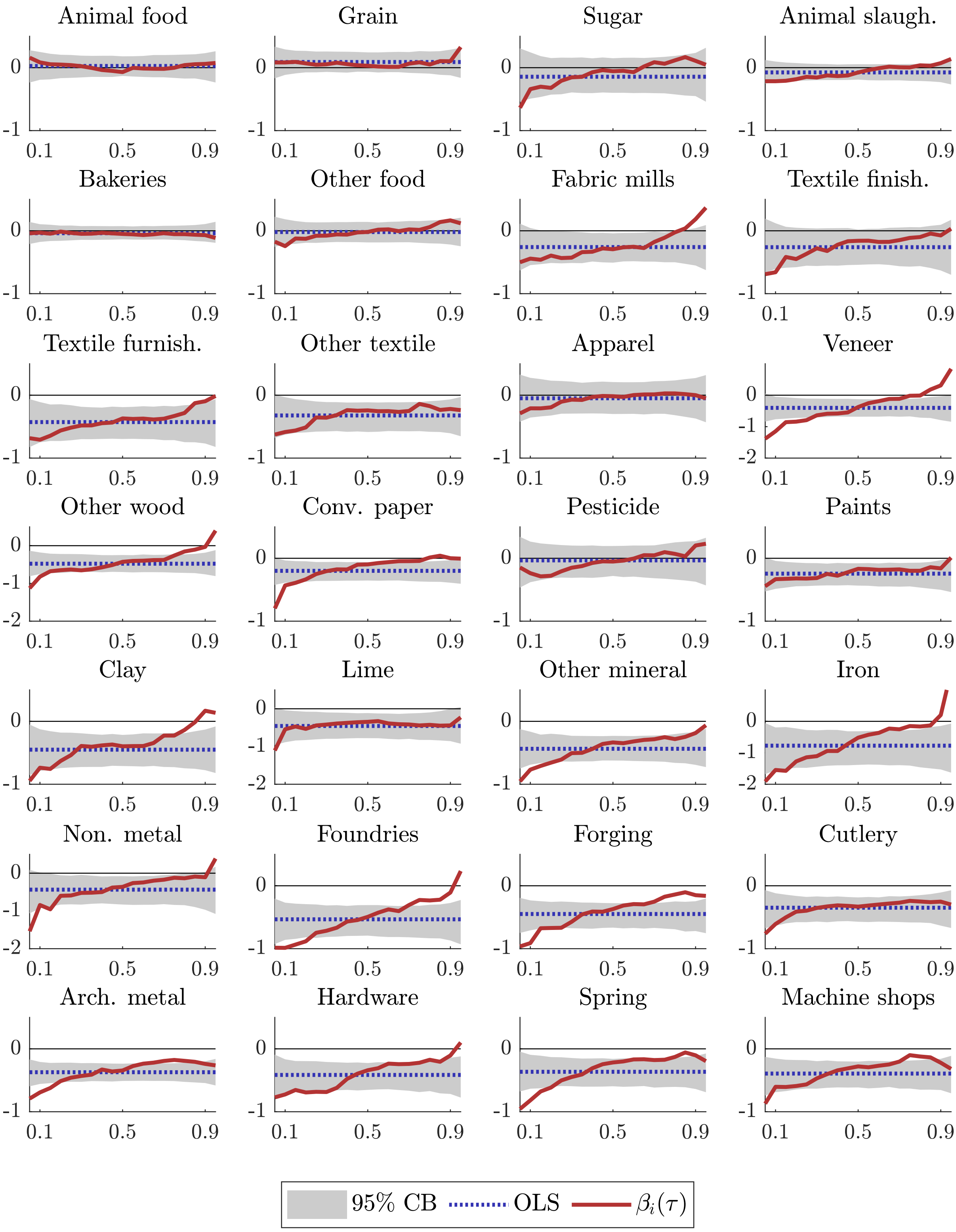


Figure H.2: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) across quantiles (with 95% bootstrap confidence bounds (CB) based on a VAR(4) model for IP and NFCI as data-generating process) for 28 industries

I Testing for slope homogeneity across industries

We consider the quantile regression slope homogeneity test of Galvao et al. (2018) to test whether the quantile slope coefficients are significantly different across industries. Since the test is performed for a fixed and given τ, we suppress the dependence on τ in this section for notational convenience. For each industry i, we denote the quantile slope coefficients as $\hat{\gamma}_i = \boldsymbol{\Xi}\hat{\boldsymbol{\theta}}_i$, where the matrix $\boldsymbol{\Xi}$ selects the K slope coefficients of interest and $\hat{\boldsymbol{\theta}}_i$ is obtained from equation (2). For a given quantile τ, we test the null hypothesis of slope homogeneity across industries $H_0 : \boldsymbol{\gamma}_{0i} = \boldsymbol{\gamma}_0$ for a fixed vector (or scalar) $\boldsymbol{\gamma}_0$ for all i, against the alternative $H_1 : \boldsymbol{\gamma}_{i0} \neq \boldsymbol{\gamma}_{j0}$ for at least some i, j.

The Swamy-type and standardized Swamy-type test statistics of Galvao et al. (2018) are respectively given by

$$\hat{S}(\tau) = \sum_{i=1}^{N} \left(\hat{\gamma}_i - \hat{\gamma}_{MD}\right)' \hat{\boldsymbol{V}}_i^{-1} \left(\hat{\gamma}_i - \hat{\gamma}_{MD}\right), \tag{I.1}$$

and

$$\hat{\Delta}(\tau) = \sqrt{N}\left(\frac{\frac{1}{N}\hat{S}(\tau) - K}{\sqrt{2K}}\right),$$

where

$$\hat{\gamma}_{MD} = \left(\sum_{i=1}^{N} \hat{\boldsymbol{V}}_i^{-1}\right)^{-1} \sum_{i=1}^{N} \hat{\boldsymbol{V}}_i^{-1}\hat{\gamma}_i,$$

is the fixed effects minimum distance (MD) estimator of Galvao and Wang (2015) and $\hat{\boldsymbol{V}}_i = \boldsymbol{\Xi}\tilde{\boldsymbol{V}}_i\boldsymbol{\Xi}'$ with $\tilde{\boldsymbol{V}}_i$ being the estimator of the covariance matrix of $\hat{\boldsymbol{\theta}}_i$, which can be obtained via the stationary bootstrap approach discussed in section 2 of the main text.[3] Then, Galvao et al. (2018) prove that $\hat{S}(\tau) \xrightarrow{d} \chi^2_{(T-h-1)K}$ and $\hat{\Delta}(\tau) \xrightarrow{d} \mathcal{N}(0,1)$ such that the tests can easily be performed.

[3]Note that the term $\hat{\boldsymbol{V}}_i^{-1}$ in equation (I.1) does not include the scaling term T as in Galvao et al. (2018) since $\tilde{\boldsymbol{V}}_i$ is the covariance matrix estimator of $\hat{\boldsymbol{\theta}}_i$ here and not of $\sqrt{T}\hat{\boldsymbol{\theta}}_i$.

J Regressions on industry characteristics

Table J.1: Regression of the NFCI quantile and mean coefficients on industry characteristics based on the total manufacturing sector (74 industries)

	Quantile					**Mean**
	5%	**25%**	**50%**	**75%**	**95%**	
Intercept	**-0.77*****	**-0.43*****	**-0.24*****	**-0.12*****	0.04	**-0.31*****
	(0.04)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)
Value added	**-0.12****	**-0.06****	0.00	**0.05****	0.16*	-0.02
	(0.06)	(0.03)	(0.03)	(0.03)	(0.07)	(0.03)
Capital intensity	**0.16****	**0.10****	**0.06****	0.00	**-0.12****	0.05
	(0.05)	(0.03)	(0.03)	(0.03)	(0.06)	(0.02)
Materials intensity	-0.08*	-0.06*	-0.02	0.01	0.06	-0.02
	(0.04)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)
Energy intensity	-0.02	0.06	0.02	-0.04	-0.02	0.01
	(0.06)	(0.03)	(0.03)	(0.03)	(0.07)	(0.02)
Production labor intensity	-0.06	-0.01	0.01	0.04	0.11*	0.00
	(0.06)	(0.03)	(0.03)	(0.03)	(0.07)	(0.03)
Overhead labor intensity	**0.29*****	**0.22*****	**0.10*****	-0.03	**-0.22****	**0.12*****
	(0.07)	(0.04)	(0.03)	(0.03)	(0.08)	(0.03)
Labor hoarding	**0.26*****	**0.13*****	**0.06*****	0.03*	0.00	**0.10*****
	(0.05)	(0.03)	(0.02)	(0.02)	(0.05)	(0.02)
Concentration ratio	-0.11	-0.05	-0.01	0.02	0.11*	-0.01
	(0.06)	(0.04)	(0.03)	(0.03)	(0.07)	(0.03)
Durability dummy	**-0.18*****	**-0.16*****	**-0.09*****	-0.03	0.04	**-0.10*****
	(0.06)	(0.03)	(0.02)	(0.02)	(0.07)	(0.02)
R^2	0.60	0.66	0.56	0.35	0.39	0.63
	(0.06)	(0.05)	(0.07)	(0.07)	(0.08)	(0.06)

Notes: This table shows the estimated coefficients of the regressions of the NFCI quantile and mean coefficients on industry characteristics based on the total manufacturing sector for the horizon $h = 3$. The bootstrap standard errors are given in parentheses. The asterisks $*$, $**$, and $***$ indicate significance at the 10%, 5% and 1% level, respectively. A bold coefficient indicates significance at the 5% level.

Table J.2: Regression of the NFCI quantile and mean coefficients on industry characteristics based on the durable goods sector (45 industries)

	Quantile					Mean
	5%	25%	50%	75%	95%	
Intercept	**-0.96*****	**-0.55*****	**-0.31*****	**-0.17*****	0.03	**-0.40*****
	(0.06)	(0.04)	(0.03)	(0.03)	(0.06)	(0.03)
Value added	-0.09	**-0.09****	-0.01	0.04*	0.19	-0.04
	(0.08)	(0.04)	(0.03)	(0.03)	(0.11)	(0.03)
Capital intensity	-0.09	0.07	0.08	0.11	0.25	0.06
	(0.14)	(0.09)	(0.08)	(0.09)	(0.17)	(0.07)
Materials intensity	**-0.23*****	**-0.11****	-0.05	0.03	0.16*	-0.06
	(0.08)	(0.04)	(0.03)	(0.03)	(0.09)	(0.03)
Energy intensity	0.07	0.09	0.02	-0.07	-0.06	0.02
	(0.08)	(0.05)	(0.04)	(0.04)	(0.10)	(0.03)
Production labor intensity	-0.14	0.04	0.06	0.11*	**0.28****	0.04
	(0.11)	(0.08)	(0.07)	(0.07)	(0.12)	(0.06)
Overhead labor intensity	0.24*	**0.28*****	**0.14****	0.03	-0.04	**0.16****
	(0.12)	(0.07)	(0.06)	(0.06)	(0.14)	(0.05)
Labor hoarding	0.03	0.05	0.04	0.05*	0.05	0.05*
	(0.06)	(0.04)	(0.03)	(0.03)	(0.05)	(0.03)
Concentration ratio	0.01	-0.02	-0.01	-0.02	-0.05	-0.01
	(0.08)	(0.04)	(0.04)	(0.04)	(0.09)	(0.03)
R^2	0.75	0.75	0.59	0.59	0.59	0.68
	(0.09)	(0.08)	(0.09)	(0.11)	(0.12)	(0.09)

Notes: This table shows the estimated coefficients of the regressions of the NFCI quantile and mean coefficients on industry characteristics based on the durable goods sector for the horizon $h = 3$. The bootstrap standard errors are given in parentheses. The asterisks $*$, $**$, and $***$ indicate significance at the 10%, 5% and 1% level, respectively. A bold coefficient indicates significance at the 5% level.

Table J.3: Regression of the NFCI quantile and mean coefficients on industry characteristics based on the nondurable goods sector (29 industries)

	Quantile					Mean
	5%	**25%**	**50%**	**75%**	**95%**	
Intercept	**-0.48*****	**-0.23*****	**-0.12*****	**-0.05*****	0.06	**-0.17*****
	(0.05)	(0.03)	(0.02)	(0.02)	(0.06)	(0.02)
Value added	-0.07	0.00	0.01	0.01	0.01	0.00
	(0.07)	(0.04)	(0.03)	(0.03)	(0.09)	(0.03)
Capital intensity	0.22	0.08	0.07	0.01	-0.27	0.04
	(0.11)	(0.07)	(0.05)	(0.05)	(0.14)	(0.05)
Materials intensity	0.03	0.00	0.01	-0.01	0.00	0.01
	(0.05)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)
Energy intensity	**-0.24*****	**-0.07****	-0.02	0.02	0.05	-0.05
	(0.08)	(0.03)	(0.03)	(0.03)	(0.07)	(0.03)
Production labor intensity	-0.02	-0.01	0.02	0.02	0.02	0.01
	(0.10)	(0.05)	(0.04)	(0.04)	(0.11)	(0.04)
Overhead labor intensity	-0.12*	-0.05	-0.02	-0.01	-0.05	-0.05
	(0.07)	(0.04)	(0.03)	(0.03)	(0.07)	(0.03)
Labor hoarding	**0.32*****	**0.12*****	0.05	0.02	-0.05	**0.10*****
	(0.07)	(0.04)	(0.03)	(0.03)	(0.08)	(0.03)
Concentration ratio	-0.32*	-0.12	-0.06	0.01	0.23	-0.07
	(0.13)	(0.08)	(0.07)	(0.07)	(0.19)	(0.06)
R^2	0.61	0.58	0.37	0.10	0.66	0.49
	(0.09)	(0.08)	(0.09)	(0.09)	(0.11)	(0.09)

Notes: This table shows the estimated coefficient of the regressions of the NFCI quantile and mean coefficients on industry characteristics based on the nondurable goods sector for the horizon $h = 3$. The bootstrap standard errors are given in parentheses. The asterisks $*$, $**$, and $***$ indicate significance at the 10%, 5% and 1% level, respectively. A bold coefficient indicates significance at the 5% level.

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