

Opschoor, Daan; van Dijk, Dick; Franses, Philip Hans

Working Paper

Heterogeneity in Manufacturing Growth Risk

Tinbergen Institute Discussion Paper, No. TI 2021-036/III

Provided in Cooperation with:

Tinbergen Institute, Amsterdam and Rotterdam

Suggested Citation: Opschoor, Daan; van Dijk, Dick; Franses, Philip Hans (2021) :
Heterogeneity in Manufacturing Growth Risk, Tinbergen Institute Discussion Paper, No. TI
2021-036/III, Tinbergen Institute, Amsterdam and Rotterdam

This Version is available at:

<https://hdl.handle.net/10419/237769>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

TI 2021-036/III
Tinbergen Institute Discussion Paper

Heterogeneity in Manufacturing Growth Risk

Daan Opschoor¹
Dick van Dijk¹
Philip Hans Franses¹

¹ Econometric Institute, Erasmus University Rotterdam

Tinbergen Institute is the graduate school and research institute in economics of Erasmus University Rotterdam, the University of Amsterdam and Vrije Universiteit Amsterdam.

Contact: discussionpapers@tinbergen.nl

More TI discussion papers can be downloaded at <https://www.tinbergen.nl>

Tinbergen Institute has two locations:

Tinbergen Institute Amsterdam
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 598 4580

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900

Heterogeneity in Manufacturing Growth Risk*

Daan Opschoor Dick van Dijk Philip Hans Franses

Econometric Institute, Erasmus University Rotterdam

May 3, 2021

Abstract

We analyze 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

*Email addresses: opschoor@ese.eur.nl (Daan Opschoor), djvandijk@ese.eur.nl (Dick van Dijk), franses@ese.eur.nl (Philip Hans Franses). We thank participants at the Econometric Institute research seminar for their helpful comments and suggestions.

1 Introduction

In light of the Great Recession, quantifying and monitoring the evolution of risks to 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 focussing on optimizing expected outcomes (Kilian and Manganelli, 2008; Sánchez and Röhn, 2016; Prasad et al., 2019).¹ 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 as a function 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 (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 as well and can offer 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 with respect to financial conditions differ across industries and how these differences can be explained. This is what we will do in this paper.

To address this issue, we use a multi-level quantile regression approach to analyze and explain the differences in growth risk across U.S. manufacturing industries and their

¹For 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/powell120200827a.htm>)

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. 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 as follows. First, we document significant heterogeneity across industries in how strongly their output growth is affected by the NFCI. For the large majority of industries, we find a pronounced nonlinear relationship between output growth and the NFCI. Deteriorating financial conditions have a much stronger negative effect on downside risks than on the central parts of the growth distribution, while upside potential is almost not affected at all. On average, a one standard deviation positive shock in the NFCI leads to a decline in the 5 percent quantile and median of three-month ahead IP growth of 0.773% and 0.237%, respectively, and an increase in the 95 percent quantile growth of 0.042%. By contrast, some industries 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. We find that the durable goods sector is more vulnerable to adverse financial conditions than the nondurable goods sector, where the average impact of the NFCI on the 5 percent quantile of three-month ahead IP growth is in fact twice as strong for durable goods industries as for nondurables. Based on all manufacturing industries, we find that large industries have more vulnerable growth, whereas capital intensive, overhead labor intensive, or in labor hoarding engaging industries have less susceptible growth. When we 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, energy intensity, overhead labor intensity and labor hoarding significantly explain part of the variation in the effects of the NFCI on downside production growth. Within the nondurable goods sector, on the other

hand, only the energy intensity explains part of the variation.

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 within the manufacturing sector that are less vulnerable to adverse shocks in the financial market.

Our work is strongly 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). 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. In addition, 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), making overhead labor intensive industries also less cyclical (Petersen and Strongin, 1996). Another important driver of cyclical fluctuations is an industry's market structure such as its concentration ratio (Domowitz et al., 1985, 1988). 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).

²For 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>)

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 could be extended to a multivariate case by means of quantile vector autoregressions (Chavleishvili and Manganelli, 2019; Falco-nio and Manganelli, 2020; Chavleishvili and Kremer, 2021) or to a data-rich environment 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.

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. 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, after which we examine which industry characteristics explain why some industries are more vulnerable to these conditions for specific parts of the growth distribution.

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 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. In addition, we extend the set-up of [Adrian et al. \(2019\)](#) 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. 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 τ th quantile of $\bar{y}_{i,t+h}$ conditional on $\mathbf{x}_{i,t} = (1, NFCI_t, y_{i,t})'$ as

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

for $i = 1, \dots, N$ and $t = 1, \dots, T - h$, where N is the number of industries and T the number of observations. 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 economic conditions, respectively, on the τ th 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 and 1. However, given the focus of policymakers 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 consider an extended quantile regression, where we add additional lags of $y_{i,t}$ as well as other macro-financial control variables. Specifically, we follow [Gilchrist and Zakrajšek \(2012\)](#) and we

³A possible way to estimate a multi-level quantile regression model in a one-step approach would be to put it in a Bayesian estimation framework, see for example [Chang \(2015\)](#).

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 G for complete details. Second, we consider the heterogeneous panel quantile regression model with 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 H for further details.

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

$$\hat{\boldsymbol{\theta}}_i(\tau) = \arg \min_{\boldsymbol{\theta}_i(\tau)} \frac{1}{T} \sum_{t=1}^{T-h} \rho_{\tau} \left(\bar{y}_{i,t+h} - \mathbf{x}'_{i,t} \boldsymbol{\theta}_i(\tau) \right), \quad i = 1, \dots, N, \quad (2)$$

where $\boldsymbol{\theta}_i(\tau) = (\alpha_i(\tau), \beta_i(\tau), \phi_i(\tau))'$ and $\rho_{\tau}(u) = u(\tau - \mathbb{I}\{u \leq 0\})$ is the standard check function of quantile regressions ([Koenker and Bassett, 1978](#)).⁴

Next, we consider in a second level, for a specific quantile τ , the cross-sectional regression of the form

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

where \mathbf{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 0 and variance 1 for interpretation purposes. We estimate this second level by plugging in the estimated quantile coefficients $\hat{\beta}_i(\tau)$ of the first-level quantile regressions and conducting ordinary least squares (OLS) estimation with [White \(1980\)](#) standard errors to deal with potential heteroskedasticity across the industries. For each industry i and quantile τ , the coefficients $\delta_k(\tau)$ for $k = 2, \dots, K+1$ measure the effect of the k th industry characteristic on the quantile regression coefficient corresponding to 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.

⁴We 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>

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.⁵ We select the industries that are available at the four-digit level of the 2012 North American Industry Classification System (NAICS).⁶ 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 A 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 markets, debt and equity markets, and the traditional and shadow banking systems.⁷ 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-maximum likelihood approach of [Doz et al. \(2012\)](#) and can be obtained from the Federal Reserve Bank of St. Louis.⁸ 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 plastic products, alumina, and motor vehicle parts, we clearly 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 in motor vehicle parts showing a much stronger response than alumina

⁵<https://www.federalreserve.gov/releases/g17/current/default.htm>

⁶We also consider disaggregation at a lower (three-digit) and higher (six-digit) NAICS level. Our results are robust to the choice of disaggregation level (see Appendix J), 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.

⁷<https://www.chicagofed.org/publications/nfci/index>

⁸<https://fred.stlouisfed.org/series/NFCI>

and especially plastics products. In fact, for dairy products this relationship seems to be nonexistent altogether. Hence, Figure 1 already indicates some heterogeneity across industries in their sensitivity to financial conditions.

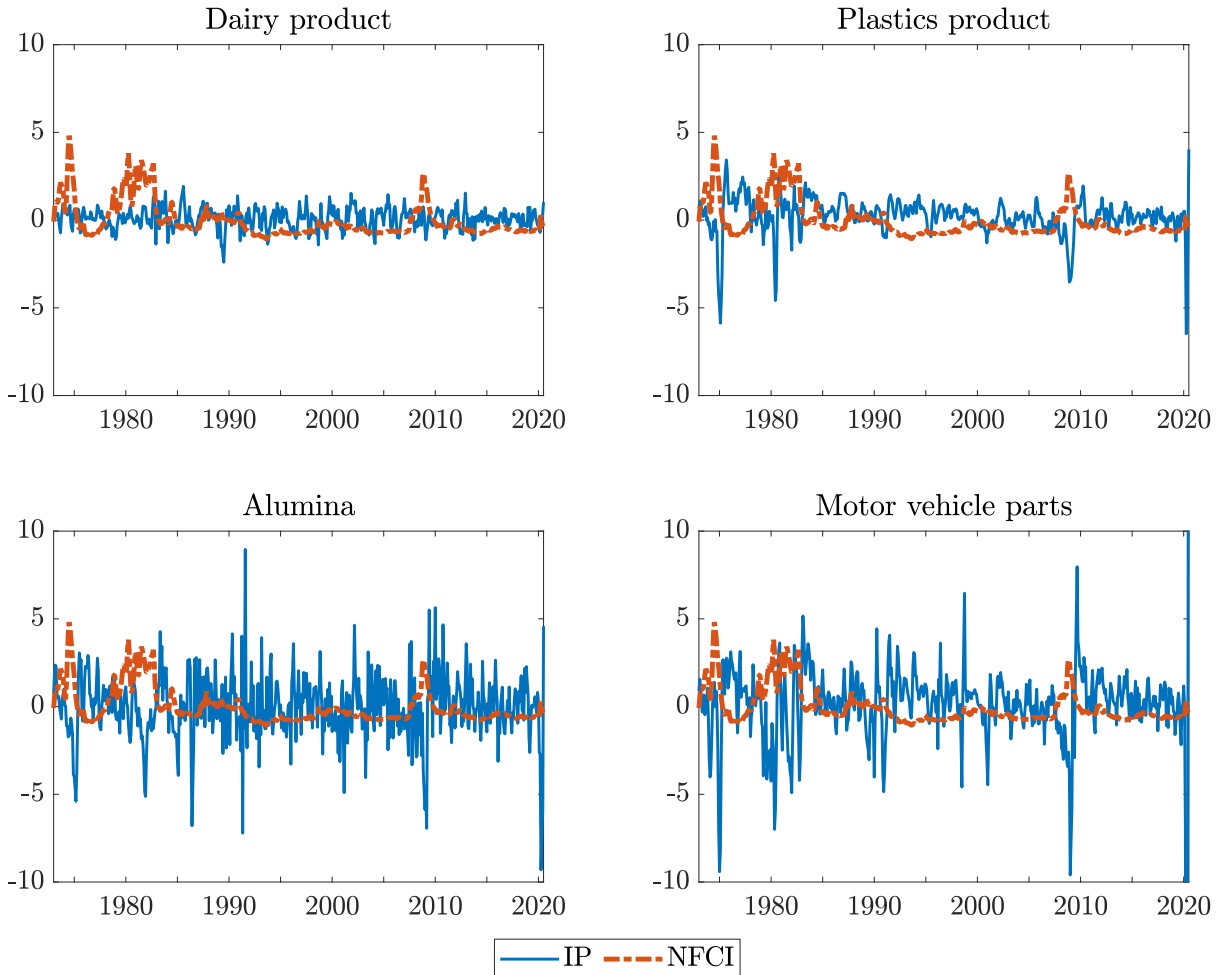


Figure 1: Time series of three-month average IP growth and the NFCI

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. These characteristics can be divided in several 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 1958-2011.⁹ We supplement this database with more recent observations over the period 2012-2018 from the Annual Survey of Manufacturers (ASM) of the U.S. Census Bureau.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 total value added of that industry. Moreover, we follow [Petersen and Strongin \(1996\)](#) by including an alternative labor hoarding measure that is computed as the negative correlation between the change in materials usage (measured as total cost of materials, including energy) and the change in production-worker hours. This implies that a correlation coefficient of 1 corresponds to no labor hoarding, which we multiply by minus 1 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 total 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 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. Moreover, we follow the recommendation of [Petersen and Strongin \(1996\)](#) to also examine a separation between the durable and nondurable goods sector to allow for different effects of these characteristics within each sector. We follow the classification of durable and non-durable goods sectors from the Federal Reserve, which results in 45 industries classified as durables and 29 industries as nondurables.¹³

⁹<https://www.nber.org/research/data/nber-ces-manufacturing-industry-database>

¹⁰<https://www.census.gov/programs-surveys/asm.html>

¹¹<https://www.bls.gov/mfp/>

¹²<https://www.census.gov/programs-surveys/economic-census.html>

¹³<https://www.federalreserve.gov/releases/g17/SandDesc/sdtab1.pdf>

Table 1 shows summary statistics of the industry characteristics.¹⁴ We observe that the energy intensities, production and overhead labor intensities, and concentration ratios are roughly similar across durable and nondurable goods sectors, with some small differences for the latter three characteristics. In contrast, the industry size, and capital and material intensities exhibit clear differences between the durable and nondurable goods sectors, particularly the mean, median and standard deviation are substantially larger for nondurable goods (except for the standard deviation of industry size). Comparing the mean and median, we observe a skewed distribution of the industry sizes and materials intensities in the durable goods sector, whereas for the nondurable goods sector the capital and materials intensities have a skewed distribution. The mean of the labor hoarding measure is -0.73 for the durable goods industries and -0.45 for nondurable goods industries, 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 -1).

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

	VA	Cap.	Mat.	Energy	ProdL	OverL	LH	CR
<i>Panel A: Total manufacturing sector (74 industries)</i>								
Mean	1.35	1.40	1.22	0.05	0.25	0.13	-0.62	0.31
Median	1.09	0.87	1.05	0.02	0.25	0.13	-0.72	0.28
Std.	1.01	1.95	0.74	0.05	0.08	0.05	0.28	0.17
<i>Panel B: Durable goods sector (45 industries)</i>								
Mean	1.24	0.82	1.06	0.05	0.27	0.15	-0.73	0.29
Median	0.91	0.76	0.87	0.02	0.26	0.15	-0.78	0.25
Std.	1.06	0.37	0.50	0.05	0.06	0.05	0.23	0.17
<i>Panel C: Nondurable goods sector (29 industries)</i>								
Mean	1.52	2.31	1.46	0.05	0.21	0.11	-0.45	0.33
Median	1.45	1.67	1.20	0.04	0.19	0.10	-0.49	0.34
Std.	0.91	2.88	0.97	0.04	0.10	0.03	0.26	0.16

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 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).

¹⁴The cross-correlations of the industry characteristics are given in Appendix B. In short, multicollinearity is not an issue at the four-digit NAICS level.

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 ($\hat{\beta}_i(\tau)$) in equation (1) for 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 I. 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 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, the average 5% quantile regression coefficient across all industries is -0.773 , while it is only -0.309 and -0.237 for the linear and 50% quantile regression coefficients, respectively. For the 5% coefficients, we find that 56 out of 74 industries (that is, 75.7%) are significantly different from zero (at the 5% significance level), whereas for the linear regression and median coefficients this is the case for 54 industries (that is, 73.0%) and 27 industries (that is, 36.5%), respectively.¹⁵ By contrast, the 95% quantile regression coefficients display a mix of positive and negative values with an average value of 0.042, where only 24 industries (that is, 32.4%) have significant coefficients. Interestingly, the industries with large negative 5% coefficients seem to have large positive 95% coefficients, although this is most obvious for iron, motor vehicles, fiber

¹⁵For details on the estimation of the asymptotic covariance matrix of the quantile regression coefficients needed to compute the p -values, see Appendix C.

and resin. The correlation between the 5% and 95% coefficients based on all industries is equal to -0.551 , where it reduces to -0.247 when we leave out iron, motor vehicles, fiber and resin. Hence, there is some weak evidence that industries with large downside production growth risk are also inclined to have more upside potential in times of tight financial conditions, albeit this upside potential is generally smaller than the increased downside risks.

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 are -0.958 , -0.312 and 0.028 , respectively, while they are -0.484 , -0.120 and 0.065 in the nondurable goods sector. Hence, the durable goods sector is, on average, twice as sensitive in the left tail of the growth distribution to adverse financial conditions than 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. We obtain that 37 out of 45 durable goods producing industries (that is, 82.2%) have significant 5% coefficients, while this holds for 19 out of 29 nondurable goods producing industries (that is, 65.5%). In addition, 84.4%, 53.5% and 35.6% of the durable goods producing industries have significant mean, median and 95% NFCI coefficients, respectively, whereas this is the case for 55.2%, 10.3% and 27.6% of the nondurable goods producing industries. Overall, the durable goods sector is more affected by the NFCI than the nondurable goods sector.

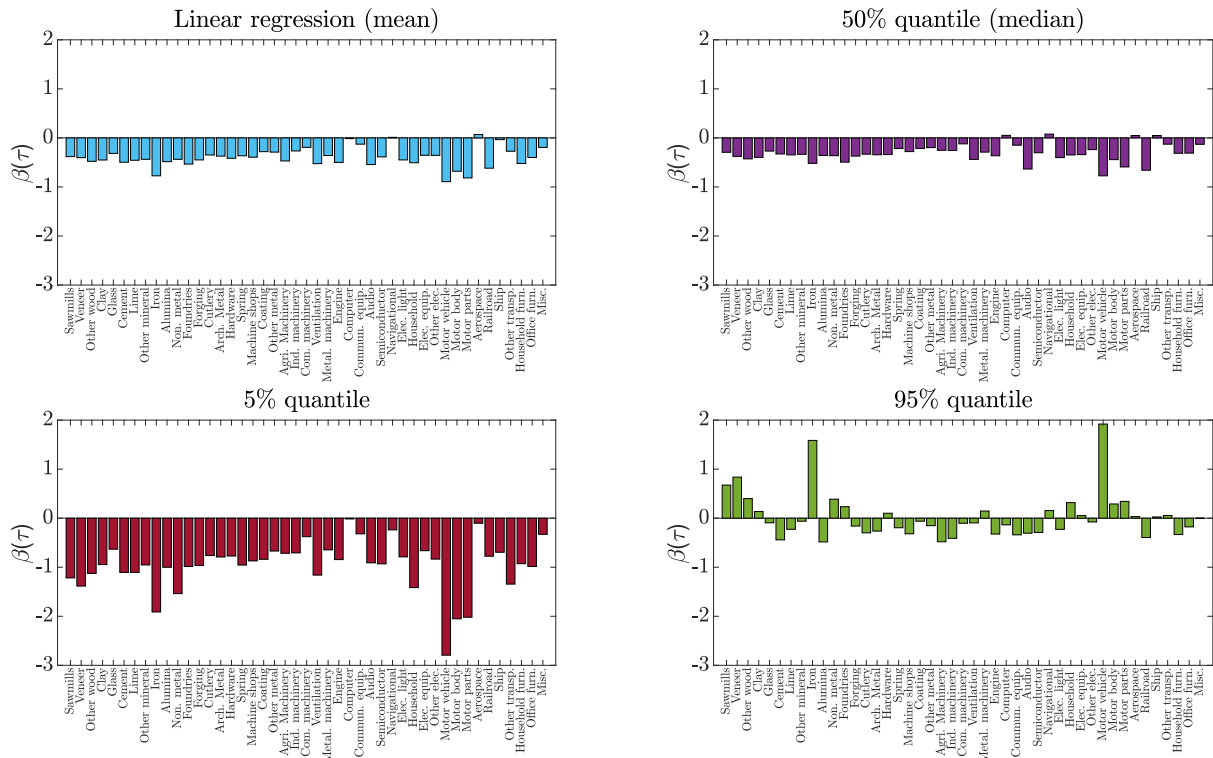


Figure 2: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for durable goods producing industries

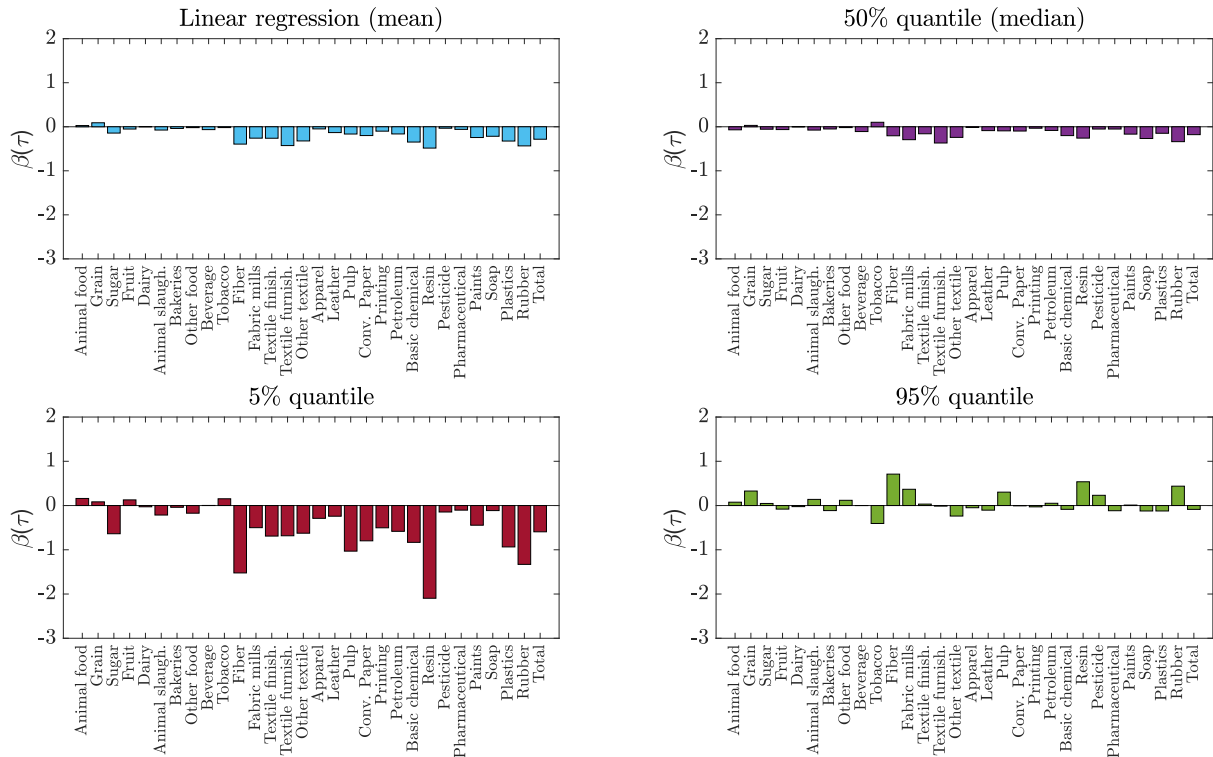


Figure 3: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for nondurable goods producing industries

The distinction between durable and nondurable goods sectors 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 5% quantile regression coefficients below -2. In contrast, the 5% coefficients for the computer and aerospace industry are both statistically indistinguishable from zero. Similarly for nondurables, the downside growth risk of resin and fiber production is strongly affected by the NFCI with coefficients below -1.5, while most of the food industries are unaffected by financial market conditions. More generally, the standard deviations of the quantile regression coefficients across all industries are 0.571, 0.182 and 0.401 for the 5%, 50% and 95% quantiles, respectively, while the interquartile ranges are 0.657, 0.259 and 0.323. Comparing these dispersion measures with the average industry and total manufacturing sector coefficients, we thus find strong heterogeneity across the industries. For the durable goods sector, the standard deviations (interquartile ranges) of the coefficients are 0.516 (0.407), 0.178 (0.148) and 0.479 (0.441) for the 5%, 50% and 95% quantiles, respectively, whereas they are 0.537 (0.629), 0.113 (0.151) and 0.239 (0.252) for the nondurable goods sector. Hence, there seems to be slightly more heterogeneity in the 5% quantile regression coefficient for the nondurable goods sector relative to the durable goods sector, while it is the other way round for the 50% and especially the 95% coefficients. Overall, we conclude that some industries have more vulnerable production growth with respect to financial conditions than others.

The quantile regression coefficients corresponding to current IP growth ($\hat{\phi}_i(\tau)$) in equation (1) are given in Appendix F. 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 no clear differences between the 5% and 50% coefficients.

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 $[0.05, 0.10, \dots, 0.90, 0.95]$ in Figure 4 for a selection of 23 industries and the total manufacturing sector. Corresponding graphs of the other industries are

shown in Appendix D. 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, the 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, 45 of the 74 industries (that is, 60.8%) 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 34 of the 45 durable industries (that is, 75.6%) have significantly different 5% coefficients from the mean estimates, whereas this holds for only 10 of the 29 nondurable industries (that is, 34.5%). 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 GDP growth. Yet, for the other industries (for example dairy, leather and computer), 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.

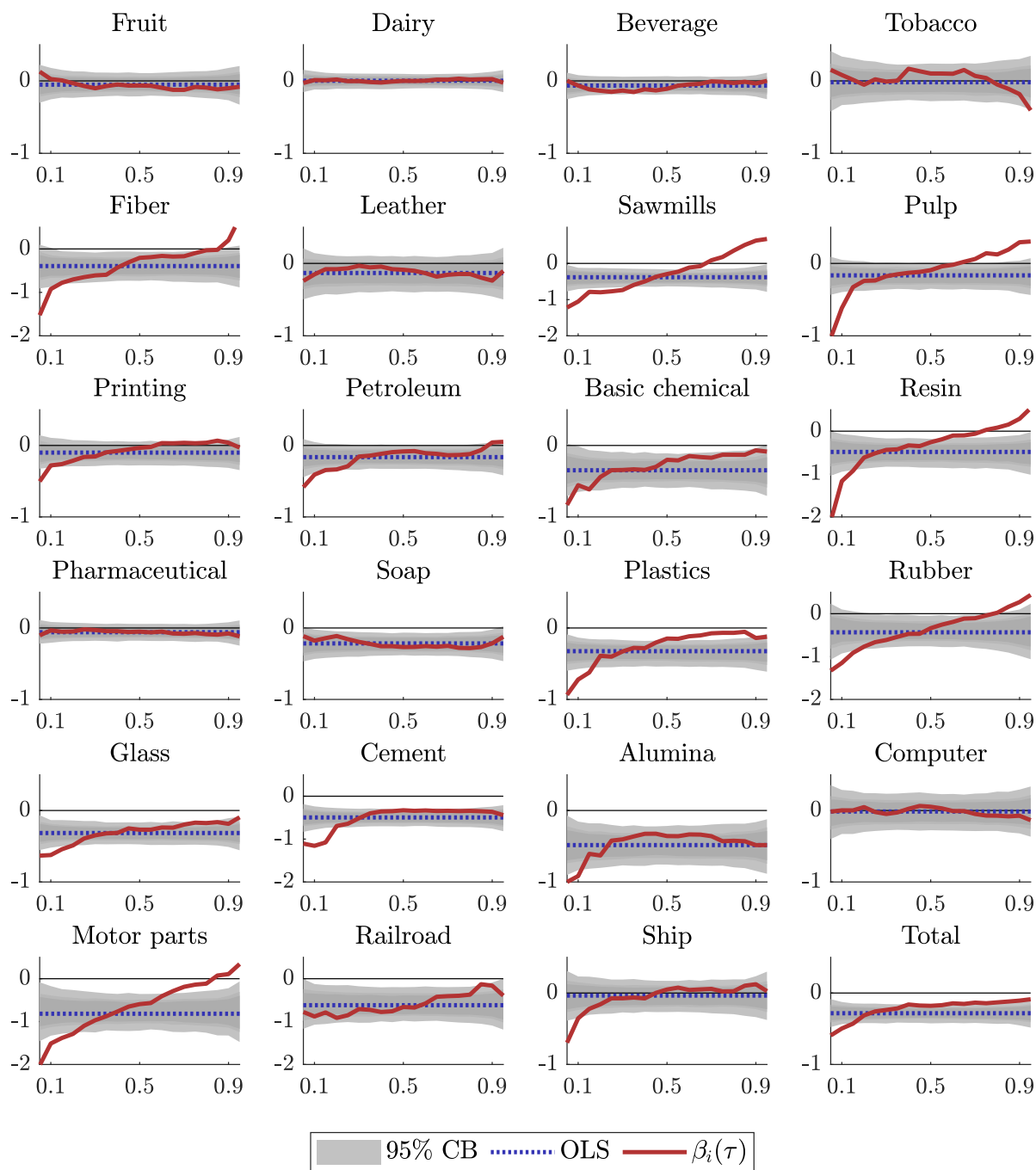


Figure 4: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) across quantiles (with 95% bootstrap confidence bounds (CB) based on a VAR(4) model for IP and NFCI as data-generating process)

To formally test whether the quantile regression coefficient estimates are different across industries, we conduct the quantile slope homogeneity test 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 this

test, see Appendix C.

Table 2 shows the p -values corresponding to these slope homogeneity tests. We see that the NFCI slope coefficients are significantly different across industries in the durable goods sector as well as the total manufacturing sector for all quantiles. For the nondurable goods sector, though, the slope coefficients are only significantly different for quantiles smaller than 50% and larger than 85%, while there is no evidence of heterogeneity for the other quantiles. In conclusion, the differences across manufacturing industries in how strongly they are affected by financial conditions are significant and we now turn to the question how these differences can be explained.

Table 2: p -values of slope homogeneity tests across industries for the NFCI coefficients

Quantile	Durable goods		Nondurable goods		All manufacturing	
	S	Δ	S	Δ	S	Δ
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	0.00	0.00	0.00	0.00	0.00	0.00
0.40	0.00	0.00	0.00	0.00	0.00	0.00
0.45	0.00	0.00	0.00	0.00	0.00	0.00
0.50	0.01	0.01	0.10	0.23	0.00	0.00
0.55	0.00	0.00	0.33	0.82	0.00	0.00
0.60	0.01	0.02	0.22	0.56	0.00	0.00
0.65	0.00	0.00	0.18	0.45	0.00	0.00
0.70	0.02	0.03	0.33	0.83	0.00	0.00
0.75	0.00	0.00	0.19	0.47	0.00	0.00
0.80	0.00	0.00	0.63	0.59	0.00	0.00
0.85	0.00	0.00	0.06	0.12	0.00	0.00
0.90	0.00	0.00	0.00	0.00	0.00	0.00
0.95	0.00	0.00	0.00	0.00	0.00	0.00
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 asymptotic variance-covariance matrix estimator is based on Galvao and Kato (2016) with the uniform kernel and the Bofinger bandwidth rule, and the lag truncation parameter is based on Yoon and Galvao (2020). 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.

4.2 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 3.

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 for most quantiles below 75%. 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% and 75% 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, we consider the correlations based on the durable goods sector. We observe that the materials and overhead labor intensities both have significant correlations across all quantiles, except the 75% quantile. More specifically, the materials intensity has a negative correlation for the 5%, 25% and 50% quantiles and a positive correlation for the 95% quantile, while it is the other way around for the overhead labor intensity. In addition, capital and production labor intensities have a significant negative correlation with the 5% quantile coefficient. Hence, there are more industry characteristics that correlate with the NFCI coefficients for lower quantiles than is the case for central or higher quantiles. For the OLS coefficients, we find correlation signs that are consistent with the predicted cyclical relationships of [Petersen and Strongin \(1996\)](#). That is, a positive correlation with the NFCI coefficient corresponds to a negative correlation with their cyclical measure, and vice versa.

Third, the nondurable goods sector generally has smaller correlation magnitudes than the durable goods sector. Nonetheless, both energy and production labor intensity are negatively and significantly correlated with the NFCI coefficients for the 5% and 25% quantiles. In contrast to the durable goods sector, capital intensity is positively correlated

with the NFCI coefficient of the nondurable goods sector for the 25% and 50% quantiles. The OLS coefficients, on the other hand, are correlated with the production labor intensity and labor hoarding measure.

Table 3: Correlations of NFCI quantile and OLS coefficients with industry characteristics

	Quantile coefficients					OLS
	5%	25%	50%	75%	95%	
<i>Panel A: All manufacturing (74 industries)</i>						
Value added	0.09	0.12	0.24	0.33	0.16	0.18
Capital intensity	0.31	0.30	0.34	0.25	-0.06	0.32
Materials intensity	-0.12	-0.11	-0.03	0.20	0.31	-0.01
Energy intensity	-0.25	-0.11	-0.12	-0.16	0.19	-0.18
Production labor intensity	-0.47	-0.45	-0.41	-0.15	0.18	-0.47
Overhead labor intensity	0.16	0.16	0.09	-0.19	-0.33	0.11
Labor hoarding	0.33	0.38	0.41	0.38	0.04	0.43
Concentration ratio	0.02	0.02	0.08	0.19	0.16	0.10
Durability	-0.41	-0.49	-0.52	-0.39	-0.05	-0.53
<i>Panel B: Durable goods (45 industries)</i>						
Value added	0.05	0.02	0.20	0.40	0.28	0.14
Capital intensity	-0.31	-0.23	-0.09	0.19	0.34	-0.16
Materials intensity	-0.68	-0.62	-0.51	0.21	0.49	-0.53
Energy intensity	-0.22	-0.10	-0.19	-0.35	0.11	-0.24
Production labor intensity	-0.34	-0.28	-0.27	0.07	0.23	-0.33
Overhead labor intensity	0.70	0.68	0.63	0.05	-0.39	0.71
Labor hoarding	0.03	0.07	0.16	0.21	0.06	0.12
Concentration ratio	-0.21	-0.17	-0.09	0.12	0.19	-0.09
<i>Panel C: Nondurable goods (29 industries)</i>						
Value added	0.02	0.17	0.21	0.06	-0.29	0.09
Capital intensity	0.36	0.39	0.45	0.18	-0.35	0.34
Materials intensity	0.05	0.03	0.11	0.02	0.21	0.14
Energy intensity	-0.48	-0.37	-0.17	0.17	0.48	-0.29
Production labor intensity	-0.41	-0.49	-0.34	-0.12	0.28	-0.40
Overhead labor intensity	-0.13	-0.17	-0.24	-0.23	-0.18	-0.22
Labor hoarding	0.33	0.46	0.34	0.29	-0.09	0.44
Concentration ratio	0.23	0.24	0.28	0.22	0.06	0.27

Notes: This table shows the correlations of the NFCI quantile and OLS coefficients with the industry characteristics at the horizon $h = 3$. 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.

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 5 shows the estimated industry-characteristic effects ($\hat{\delta}_i(\tau)$) on the NFCI coefficients based on all 74 industries in the manufacturing sector across quantiles with the corresponding 95% confidence intervals. 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 higher quantiles. This means that the downside production growth of large or durable goods producing industries is, on average, more vulnerable to adverse financial conditions than for small or nondurable goods producing industries. The 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 cyclical 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)

¹⁶The complete tables with estimated regression coefficients and R^2 's are given in Appendix E

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 and middle 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.

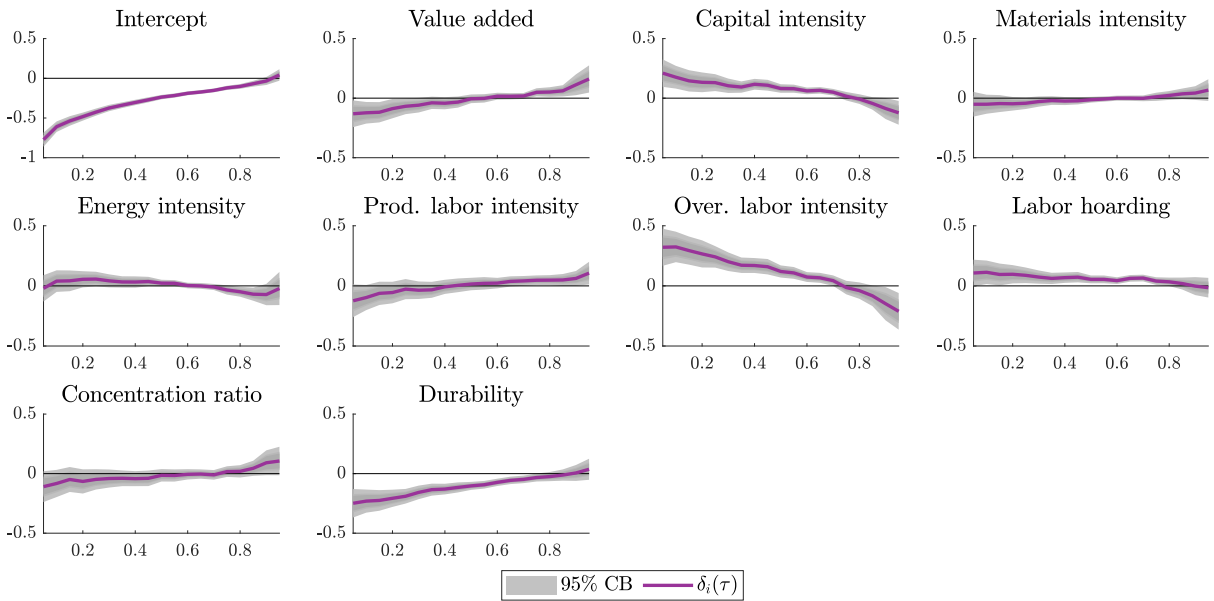


Figure 5: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles based on all 74 industries in the manufacturing sector (with 95% confidence bounds (CB) based on White standard errors)

Next, we consider the estimated industry-characteristic effects based on the 45 industries in the durable goods sector in Figure 6. 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 negative effect on low quantile NFCI coefficients in the durable goods sector, whereas overhead labor intensity and labor hoarding still have a positive effect. In other words, large durable goods producing industries have more vulnerable

growth, while overhead labor intensive or in labor hoarding engaging durable goods producing industries are less vulnerable. However, for the durable goods sector 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 relation 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. Finally, we also find a significant, albeit small, positive effect of energy intensity for some lower quantiles. This is the opposite result of the predicted relation between energy intensity and industry cyclicalities proposed by [Petersen and Strongin \(1996\)](#). A possible explanation for this difference follows from [Deichmann et al. \(2019\)](#), who show that the negative relation between energy intensity and economic growth has become less steep during the past 20 years due to changes in energy efficiency in high income countries such as the U.S. Indeed, [Evert and Schwartzman \(2017\)](#) find that energy intensive industries are not more or less correlated with the business cycle than low energy intensity industries, confirming a possibly flatter relationship relative to what [Petersen and Strongin \(1996\)](#) found.

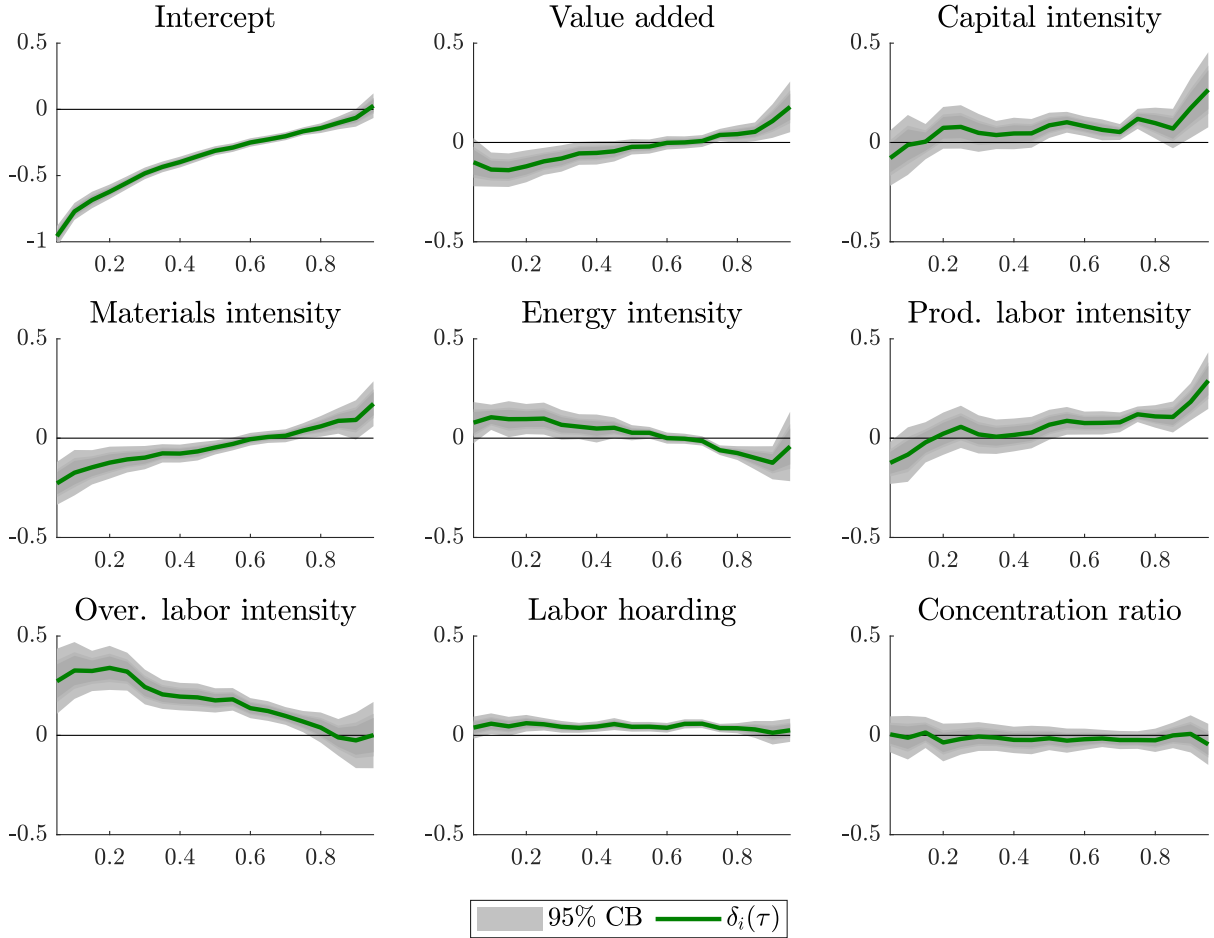


Figure 6: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the durable goods sector (with 95% confidence bounds (CB) based on White standard errors)

Moving to the industry effects based on the 29 industries in the the nondurable goods sector in Figure 7, we find that the intercept is still negative across quantiles, although less strong than for the durable goods sector. Moreover, industry size, materials intensity, production and overhead labor intensity and labor hoarding are all insignificant across the entire range of quantiles. For lower quantiles, only energy intensity seems to have a significant negative effect, while for higher quantiles only capital intensity and concentration ratio have significant effects. One reason that the industry characteristics are not able to explain the differences in the NFCI coefficients within the nondurable goods sector follows from the fact that these industries are generally less affected by financial conditions (see Figure 3). Indeed, [Petersen and Strongin \(1996\)](#) also find that they are not able to explain why some industries in the nondurable goods sector are more cyclical than others.

When comparing the effects in the durable goods sector with the nondurable goods sector, we clearly observe substantial differences. For example, the energy intensity has a positive effect on the low quantile NFCI coefficients for the durable goods sector, while it is negative for the nondurable goods sector. Moreover, the effects of capital intensity are also reversed, albeit being not statistically significant for most quantiles. Such a reversal could, for instance, follow from the fact that the nondurable goods sector is more capital intensive than the durable goods sector (see Table 1). Consequently, this changes the anchor point from which the industry-characteristic effect is evaluated.

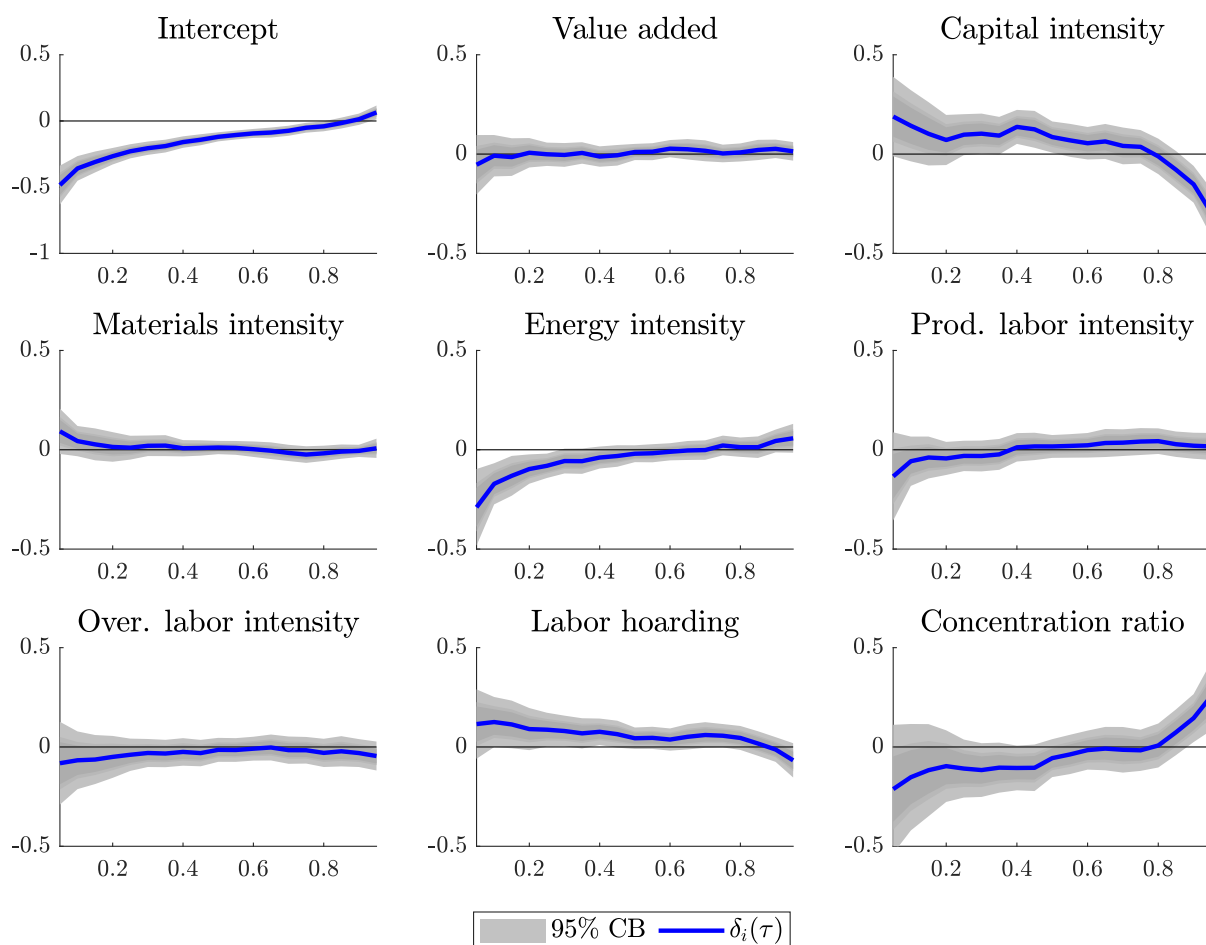


Figure 7: Estimated industry characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the nondurable goods sector (with 95% confidence bounds (CB) based on White standard errors)

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 also analyzed how this heterogeneity can be explained by industry characteristics such as size and labor hoarding. In particular, we employed industry-specific quantile regressions to link output growth risk with current financial and economic conditions, after which we link the corresponding quantile 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 intensity is an important feature explaining the differences in downside growth risk in the durable goods sector, whereas the energy intensity is important 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.

References

- ACEMOGLU, D., V. M. CARVALHO, A. OZDAGLAR, AND A. TAHBAZ-SALEHI (2012): “The Network Origins of Aggregate Fluctuations,” *Econometrica*, 80, 1977–2016.
- ADAMS, P. A., T. ADRIAN, N. BOYARCHENKO, AND D. GIANNONE (2021): “Forecasting macroeconomic risks,” *International Journal of Forecasting*.
- ADRIAN, T., N. BOYARCHENKO, AND D. GIANNONE (2019): “Vulnerable Growth,” *American Economic Review*, 109, 1263–1289.
- (2021): “Multimodality in Macroeconomic Dynamics,” *International Economic Review*, Forthcoming.
- ADRIAN, T., F. GRINBERG, N. LIANG, AND S. MALIK (2018): “The Term Structure of Growth-at-Risk,” *American Economic Journal: Macroeconomics*, Forthcoming.
- AMENC, N., M. ESAKIA, F. GOLTZ, AND B. LUYTEN (2019): “Macroeconomic Risks in Equity Factor Investing,” *The Journal of Portfolio Management*, 45, 39–60.
- ANDO, T. AND J. BAI (2020): “Quantile Co-Movement in Financial Markets: A Panel Quantile Model With Unobserved Heterogeneity,” *Journal of the American Statistical Association*, 115, 266–279.
- ARELLANO, C., Y. BAI, AND P. J. KEHOE (2018): “Financial Frictions and Fluctuations in Volatility,” *Journal of Political Economy*, 127, 2049–2103.
- BAPTIST, S. AND C. HEPBURN (2013): “Intermediate inputs and economic productivity,” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 371, 20110565.
- BARTELSMAN, E. J. AND W. GRAY (1996): “The NBER Manufacturing Productivity Database,” Working Paper 205, National Bureau of Economic Research.
- BECKER, G. S. (1962): “Investment in Human Capital: A Theoretical Analysis,” *Journal of Political Economy*, 70, 9–49.
- BERMAN, J. AND J. PFLEEGER (1997): “Which industries are sensitive to business cycles?” *Monthly Labor Review*, 120, 19–25.

- BERNANKE, B. S. (1983): “Irreversibility, Uncertainty, and Cyclical Investment,” *The Quarterly Journal of Economics*, 98, 85–106.
- BERNANKE, B. S., M. GERTLER, AND S. GILCHRIST (1999): “The financial accelerator in a quantitative business cycle framework,” in *Handbook of Macroeconomics*, Elsevier, vol. 1, 1341–1393.
- BLOMQUIST, J. AND J. WESTERLUND (2013): “Testing slope homogeneity in large panels with serial correlation,” *Economics Letters*, 121, 374–378.
- BLOOM, N. (2014): “Fluctuations in Uncertainty,” *Journal of Economic Perspectives*, 28, 153–176.
- BRAUN, M. AND B. LARRAIN (2005): “Finance and the Business Cycle: International, Inter-Industry Evidence,” *The Journal of Finance*, 60, 1097–1128.
- BRAVE, S. AND R. BUTTERS (2011): “Monitoring financial stability: a financial conditions index approach,” *Economic Perspectives*, 35, 22–43.
- BROWNLEES, C. AND A. B. M. SOUZA (2020): “Backtesting global Growth-at-Risk,” *Journal of Monetary Economics*, Forthcoming.
- CAMACHO, M. AND D. LEIVA-LEON (2019): “The Propagation of Industrial Business Cycles,” *Macroeconomic Dynamics*, 23, 144–177.
- CARRIERO, A., T. E. CLARK, AND M. MARCELLINO (2020a): “Capturing Macroeconomic Tail Risks with Bayesian Vector Autoregressions,” Working Paper 20-02, Federal Reserve Bank of Cleveland.
- (2020b): “Nowcasting Tail Risks to Economic Activity with Many Indicators,” Working Paper 20-13, Federal Reserve Bank of Cleveland.
- CARVALHO, V. AND X. GABAIX (2013): “The Great Diversification and its Undoing,” *The American Economic Review*, 103, 1697–1727.
- CHANG, C.-C. (2015): “Bayesian Multi Level Quantile Regression for Logitudinal Data,” Ph.D. Dissertation, University of Southern California, United States California.

- CHANG, Y. AND S. HWANG (2015): “Asymmetric Phase Shifts in U.S. Industrial Production Cycles,” *Review of Economics and Statistics*, 97, 116–133.
- CHAVLEISHVILI, S. AND M. KREMER (2021): “Measuring Systemic Financial Stress and its Impact on the Macroeconomy,” SSRN Scholarly Paper ID 3766928, Social Science Research Network, Rochester, NY.
- CHAVLEISHVILI, S. AND S. MANGANELLI (2019): “Forecasting and Stress Testing with Quantile Vector Autoregression,” ECB Working Paper 2330.
- CHEN, L., J. J. DOLADO, AND J. GONZALO (2021): “Quantile Factor Models,” *Econometrica*, 89, 875–910.
- COOK, T. AND T. DOH (2019): “Assessing Macroeconomic Tail Risks in a Data-Rich Environment,” *The Federal Reserve Bank of Kansas City Research Working Papers*.
- DE SANTIS, R. A. AND W. VAN DER VEKEN (2020): “Forecasting macroeconomic risk in real time: Great and Covid-19 Recessions,” Tech. Rep. 2436, European Central Bank.
- DEDOLA, L. AND F. LIPPI (2005): “The monetary transmission mechanism: Evidence from the industries of five OECD countries,” *European Economic Review*, 49, 1543–1569.
- DEICHMANN, U., A. REUTER, S. VOLLMER, AND F. ZHANG (2019): “The relationship between energy intensity and economic growth: New evidence from a multi-country multi-sectorial dataset,” *World Development*, 124, 104664.
- DELLE MONACHE, D., A. DE POLIS, AND I. PETRELLA (2020): “Modeling and Forecasting Macroeconomic Downside Risk,” SSRN Scholarly Paper ID 3674885, Social Science Research Network, Rochester, NY.
- DOMOWITZ, I., R. G. HUBBARD, AND B. C. PETERSEN (1985): “Industry margins and the business cycle: Some new microeconomic evidence,” *Economics Letters*, 19, 73–77.
- (1988): “Market Structure and Cyclical Fluctuations in U.S. Manufacturing,” *The Review of Economics and Statistics*, 70, 55–66.

- DOZ, C., D. GIANNONE, AND L. REICHLIN (2012): “A Quasi-Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models,” *The Review of Economics and Statistics*, 94, 1014–1024.
- EVERT, J. AND F. SCHWARTZMAN (2017): “The Heterogeneous Business-Cycle Behavior of Industrial Production,” *Economic Quarterly*, 102, 227–252.
- FALCONIO, A. AND S. MANGANELLI (2020): “Financial conditions, business cycle fluctuations and growth at risk,” Tech. Rep. 2470, European Central Bank.
- FIGUERES, J. M. AND M. JAROCIŃSKI (2020): “Vulnerable growth in the euro area: Measuring the financial conditions,” *Economics Letters*, 191, 109126.
- FOERSTER, A. T., P.-D. G. SARTE, AND M. W. WATSON (2011): “Sectoral versus Aggregate Shocks: A Structural Factor Analysis of Industrial Production,” *Journal of Political Economy*, 119, 1–38.
- FOK, D., D. V. DIJK, AND P. H. FRANSES (2005): “A multi-level panel STAR model for US manufacturing sectors,” *Journal of Applied Econometrics*, 20, 811–827.
- GALVAO, A. F., T. JUHL, G. MONTES-ROJAS, AND J. OLMO (2018): “Testing Slope Homogeneity in Quantile Regression Panel Data with an Application to the Cross-Section of Stock Returns,” *Journal of Financial Econometrics*, 16, 211–243.
- GALVAO, A. F. AND K. KATO (2016): “Smoothed quantile regression for panel data,” *Journal of Econometrics*, 193, 92–112.
- GIGLIO, S., B. KELLY, AND S. PRUITT (2016): “Systemic risk and the macroeconomy: An empirical evaluation,” *Journal of Financial Economics*, 119, 457–471.
- GILCHRIST, S. AND E. ZAKRAJŠEK (2012): “Credit Spreads and Business Cycle Fluctuations,” *American Economic Review*, 102, 1692–1720.
- KILIAN, L. AND S. MANGANELLI (2008): “The Central Banker as a Risk Manager: Estimating the Federal Reserve’s Preferences under Greenspan,” *Journal of Money, Credit and Banking*, 40, 1103–1129.
- KOENKER, R. AND G. BASSETT (1978): “Regression Quantiles,” *Econometrica*, 46, 33.

- KORENOK, O., B. MIZRACH, AND S. RADCHENKO (2009): “A Note on Demand and Supply Factors in Manufacturing Output Asymmetries,” *Macroeconomic Dynamics*, 13, 263–277.
- LORIA, F., C. MATTHES, AND D. ZHANG (2019): “Assessing Macroeconomic Tail Risk,” .
- LUCAS, R. E. (1977): “Understanding business cycles,” *Carnegie-Rochester Conference Series on Public Policy*, 5, 7–29.
- MITCHELL, W. C. (1951): “What Happens during Business Cycles: A Progress Report,” NBER Books, National Bureau of Economic Research, Inc.
- OECD, ed. (2003): *The sources of economic growth in OECD countries*, Paris, France: OECD Publishing.
- OI, W. Y. (1962): “Labor as a Quasi-Fixed Factor,” *Journal of Political Economy*, 70, 538–555.
- PARSONS, D. O. (1986): “The employment relationship: Job attachment, work effort, and the nature of contracts,” in *Handbook of Labor Economics*, Elsevier, vol. 2, 789–848.
- PESARAN, M. H. AND T. YAMAGATA (2008): “Testing slope homogeneity in large panels,” *Journal of Econometrics*, 142, 50–93.
- PETERSEN, B. AND S. STRONGIN (1996): “Why Are Some Industries More Cyclical Than Others?” *Journal of Business & Economic Statistics*, 14, 189–198.
- PLAGBORG-MØLLER, M., L. REICHLIN, G. RICCO, AND T. HASENZAGL (2020): “When is Growth at Risk?” *Brookings Papers on Economic Activity*, 2020.
- PRASAD, A., S. ELEKDAG, P. JEASAKUL, R. LAFARGUETTE, A. ALTER, A. XIAOCHEN FENG, AND C. WANG (2019): “Growth at Risk: Concept and Application in IMF Country Surveillance,” *IMF Working Papers*, 19.
- REICHLIN, L., G. RICCO, AND T. HASENZAGL (2020): “Financial Variables as Predictors of Real Growth Vulnerability,” Tech. Rep. 14322, C.E.P.R. Discussion Papers.

- ROSEN, S. (1968): “Short-Run Employment Variation on Class-I Railroads in the U.S., 1947-1963,” *Econometrica*, 36, 511–529.
- ROTEMBERG, J. J. AND L. H. SUMMERS (1990): “Inflexible Prices and Procyclical Productivity,” *The Quarterly Journal of Economics*, 105, 851–874.
- SWAMY, P. A. V. B. (1970): “Efficient Inference in a Random Coefficient Regression Model,” *Econometrica*, 38, 311–323.
- SÁNCHEZ, A. C. AND O. RÖHN (2016): “How do policies influence GDP tail risks?” OECD Economics Department Working Papers 1339.
- WHITE, H. (1980): “A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity,” *Econometrica*, 48, 817–838.
- YOON, J. AND A. F. GALVAO (2020): “Cluster robust covariance matrix estimation in panel quantile regression with individual fixed effects,” *Quantitative Economics*, 11, 579–608.

Heterogeneity in Manufacturing Growth Risk: A Multi-level Quantile Regression approach

Online Appendix

Daan Opschoor

Dick van Dijk

Philip Hans Franses

May 3, 2021

Contents

A	Manufacturing industries	1
B	Cross-correlations of industry characteristics	5
C	Testing for slope homogeneity across industries	6
D	Additional NFCI quantile coefficient estimates	9
E	Regressions on industry characteristics	11
F	Results of current IP growth	14
G	Controlling for additional variables	16
H	Controlling for unobserved heterogeneity	21
I	Alternative horizons	25
I.1	Six months ahead ($h = 6$)	25
I.2	One year ahead ($h = 12$)	28
J	Alternative NAICS disaggregation levels	31
J.1	Three-digit NAICS level	31
J.2	Six-digit NAICS level	33

A Manufacturing industries

Table A.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

Table A.1: Continued

Industries	NAICS Code	Selection		
		3-digit	4-digit	6-digit
Paper	322	V		
Pulp, paper, and paperboard mills	3221		V	
Pulp mills	32211			V
Paper mills	32212			V
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

Table A.1: Continued

Industries	NAICS Code	Selection		
		3-digit	4-digit	6-digit
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 and processing	3314		V	V
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

Table A.1: Continued

Industries	NAICS Code	Selection		
		3-digit	4-digit	6-digit
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	
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			

B Cross-correlations of industry characteristics

Table B.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 overhead labor intensity. Therefore, we remove the production labor intensity in the regression of the three-digit NAICS level, which brings down the VIFs to a sufficient level.

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

	Correlations									VIF
<i>Panel A: Three-digit NAICS (21 industries)</i>										
	VA	Cap.	Mat.	Energy	ProdL	OverL	LH	CR	Dur.	
VA	1.00									2.01
Cap.	0.07	1.00								11.66
Mat.	-0.07	0.48	1.00							1.93
Energy	-0.12	0.26	0.58	1.00						3.11
ProdL	-0.44	-0.81	-0.30	-0.11	1.00					10.90
OverL	0.29	-0.54	-0.50	-0.62	0.17	1.00				5.66
LH	0.12	0.68	0.30	0.06	-0.71	-0.35	1.00			2.95
CR	-0.03	0.73	0.46	0.25	-0.50	-0.41	0.44	1.00		2.52
Dur.	0.23	-0.39	-0.27	-0.11	0.19	0.53	-0.24	-0.36	1.00	1.84
<i>Panel A: Four-digit NAICS (74 industries)</i>										
	VA	Cap.	Mat.	Energy	ProdL	OverL	LH	CR	Dur.	
VA	1.00									1.24
Cap.	0.09	1.00								2.56
Mat.	-0.01	0.11	1.00							1.29
Energy	-0.12	0.02	0.25	1.00						1.37
ProdL	-0.30	-0.58	-0.11	0.02	1.00					2.36
OverL	0.22	-0.47	-0.37	-0.44	0.12	1.00				2.61
LH	0.16	0.33	0.29	0.06	-0.54	-0.34	1.00			1.81
CR	-0.01	0.57	0.25	0.09	-0.44	-0.33	0.31	1.00		1.73
Dur.	-0.13	-0.38	-0.27	-0.07	0.38	0.46	-0.49	-0.13	1.00	1.74
<i>Panel A: Six-digit NAICS (101 industries)</i>										
	VA	Cap.	Mat.	Energy	ProdL	OverL	LH	CR	Dur.	
VA	1.00									1.26
Cap.	-	-								
Mat.	-0.13	-	1.00							1.24
Energy	-0.22	-	0.05	1.00						1.26
ProdL	-0.18	-	-0.08	-0.15	1.00					1.71
OverL	0.33	-	-0.32	-0.42	0.16	1.00				1.91
LH	0.07	-	0.21	0.13	-0.48	-0.32	1.00			1.54
CR	-0.19	-	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	-0.46	-0.23	1.00	1.58

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](#))

C 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 $\hat{\gamma}_i = \Xi \hat{\theta}_i$, where the matrix Ξ selects the K slope coefficients of interest and $\hat{\theta}_i$ is obtained from equation (2). For a given quantile τ , we test the null hypothesis of slope homogeneity across industries $H_0 : \gamma_{0i} = \gamma_0$ for a fixed vector (or scalar) γ_0 for all i , against the alternative $H_1 : \gamma_{i0} \neq \gamma_{j0}$ for at least some i, j .

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

$$\hat{S}(\tau) = \sum_{i=1}^N (\hat{\gamma}_i - \hat{\gamma}_{MD})' \left(\frac{\hat{\mathbf{V}}_i}{T-h} \right) (\hat{\gamma}_i - \hat{\gamma}_{MD}),$$

and

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

where

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

is the fixed effects minimum distance (MD) estimator of Galvao and Wang (2015) and $\hat{\mathbf{V}}_i = \Xi \tilde{\mathbf{V}}_i \Xi'$ with $\tilde{\mathbf{V}}_i$ being a consistent estimator of the asymptotic variance-covariance matrix of the quantile regression coefficients. Then, Galvao et al. (2018) prove that $\hat{S}(\tau) \xrightarrow{d} \chi_{(T-h-1)K}^2$ and $\hat{\Delta}(\tau) \xrightarrow{d} \mathcal{N}(0, 1)$ such that the tests can easily be performed.

To estimate the asymptotic variance-covariance matrix of the quantile regression coefficients, we consider the consistent estimator proposed by Galvao and Kato (2016),

i.e.

$$\begin{aligned}\tilde{\mathbf{V}}_i &= \hat{\mathbf{\Gamma}}_i^{-1} \hat{\mathbf{\Omega}}_i \hat{\mathbf{\Gamma}}_i^{-1}, \\ \hat{\mathbf{\Gamma}}_i &= \frac{1}{T-h} \sum_{t=1}^{T-h} K_{B_{T-h}}(\hat{u}_{i,t}) \mathbf{x}_{i,t} \mathbf{x}'_{i,t}, \\ \hat{\mathbf{\Omega}}_i &= \frac{\tau(1-\tau)}{T-h} \sum_{t=1}^{T-h} \mathbf{x}_{i,t} \mathbf{x}'_{i,t} + \sum_{1 \leq |j| \leq M_{T-h}} \left(1 - \frac{|j|}{T-h}\right) \\ &\quad \times \left[\frac{1}{T-h} \sum_{t=\max\{1, -j+1\}}^{\min\{T-h, T-h-j\}} (\tau - \mathbb{I}(\hat{u}_{i,t} \leq 0)) (\tau - \mathbb{I}(\hat{u}_{i,t+j} \leq 0)) \mathbf{x}_{i,t} \mathbf{x}'_{i,t+j} \right],\end{aligned}$$

where $\hat{u}_{i,t} = y_{i,t} - \mathbf{x}'_{i,t} \hat{\boldsymbol{\theta}}_i$ and $K_{B_{T-h}}(\cdot) = (1/B_{T-h})K(\cdot/B_{T-h})$.

We follow [Kato \(2012\)](#) and take the uniform kernel $K(u) = \frac{1}{2}\mathbb{I}(|u| \leq 0)$ with either the [Bofinger \(1975\)](#) or [Hall and Sheather \(1988\)](#) bandwidth rule to determine B_{T-h} . More specifically, for a given sample size n , the Bofinger bandwidth rule is

$$B_n = n^{-1/5} \left[\frac{4.5\phi^4(\Phi^{-1}(\tau))}{(2\Phi^{-1}(\tau)^2 + 1)^2} \right]^{1/5},$$

while the Hall-Sheather bandwidth rule is

$$B_n = n^{-1/3} z_\alpha^{2/3} \left[\frac{1.5\phi^2(\Phi^{-1}(\tau))}{(2\Phi^{-1}(\tau)^2 + 1)} \right]^{1/3},$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal probability and cumulative density functions, respectively, and z_α satisfies $\Phi(z_\alpha) = 1 - \frac{\alpha}{2}$ with α denoting the desired size of the test, which we set equal to 0.05.¹

Lastly, we follow the approach of [Andrews \(1991\)](#), which is augmented for quantile regressions by [Yoon and Galvao \(2020\)](#), to determine the lag truncation parameter M_{T-h} of the Bartlett kernel. More specifically, for a given sample size n , the bandwidth selection rule is $\hat{M}_n = 1.1447(\hat{\alpha}(1)n)^{1/3}$, where $\hat{\alpha}(1)$ is estimated based on an approximating parametric model for $\mathbf{z}_{i,t} = (\tau - \mathbb{I}(\hat{u}_{i,t} \leq 0)) \mathbf{x}_{i,t}$. We follow [Yoon and Galvao \(2020\)](#) and consider an AR(1) model for each element $z_{i,t,j}$ (with different parameters for each j)

¹In the main text, we use the Bofinger bandwidth rule, but unreported results show that the results are qualitatively similar for the Hall and Sheather bandwidth rule.

such that

$$\hat{\alpha}(1) = \sum_{j=2}^J \frac{4\hat{\rho}_j^2 \hat{\sigma}_j^4}{(1 - \hat{\rho}_j)^6 (1 + \hat{\rho}_j)^2} \bigg/ \sum_{j=2}^J \frac{\hat{\sigma}_j^4}{(1 - \hat{\rho}_j)^4},$$

where $\hat{\rho}_j$ and $\hat{\sigma}_j^2$ denote the autoregressive and innovation variance parameters, respectively, of the AR(1) processes of the elements $z_{i,t,j}$ for $j = 2, \dots, J$. Note that we start at $j = 2$ and hence do not include the intercept of the quantile regression.

D Additional NFCI quantile coefficient estimates

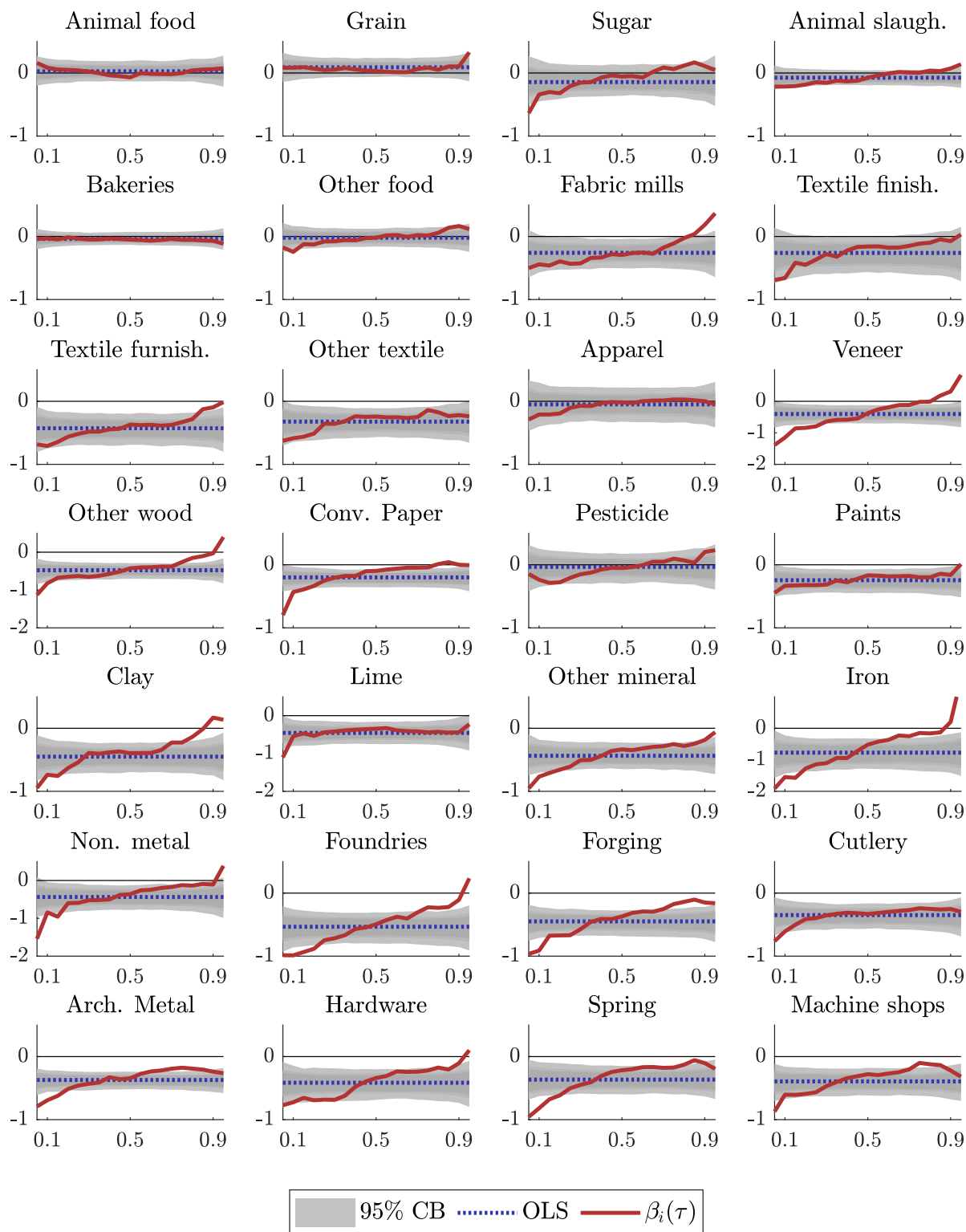


Figure D.1: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) across quantiles (with 95% bootstrap confidence bounds (CB) based on a VAR(4) model for IP and NFCI as data-generating process)

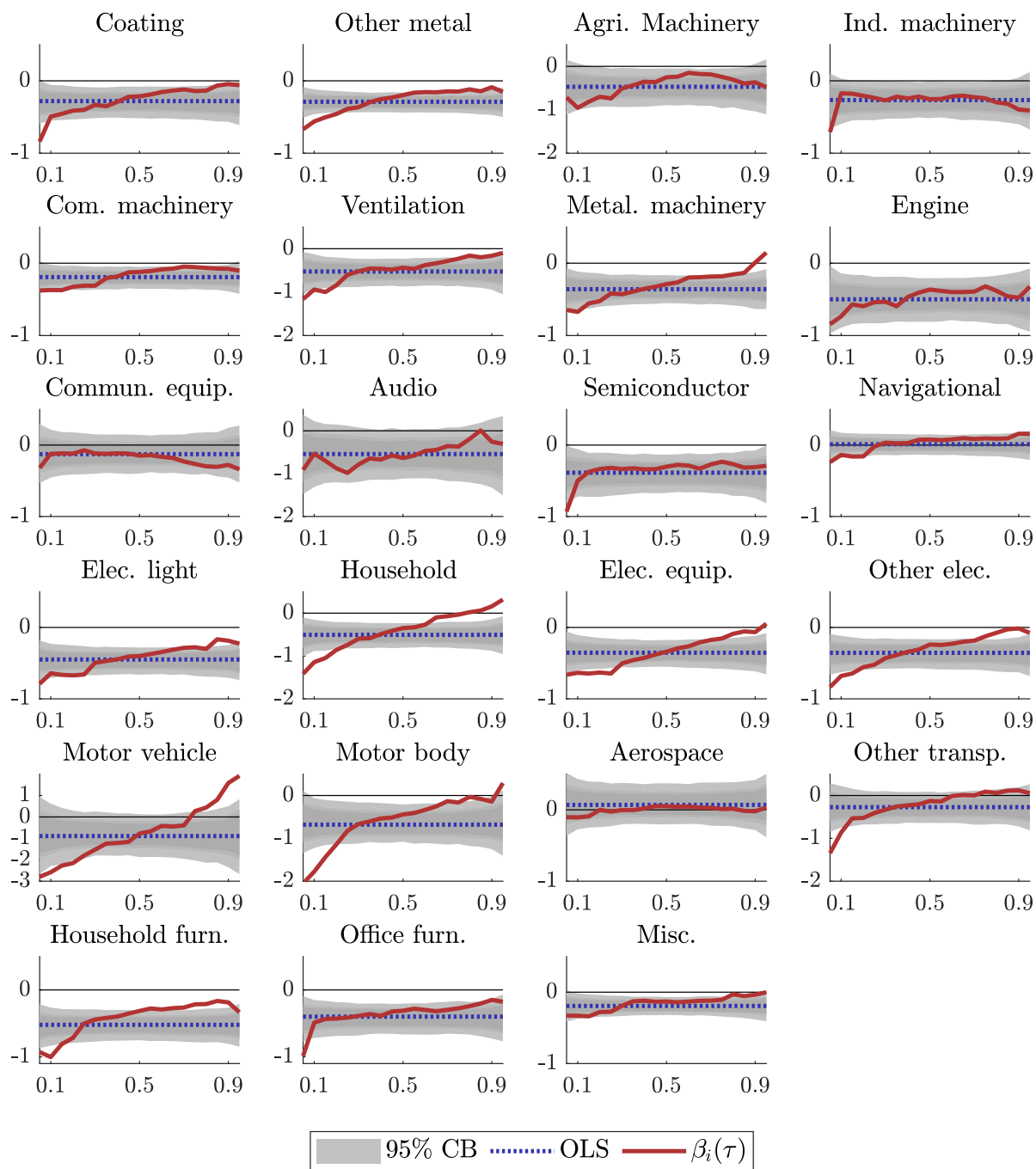


Figure D.2: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) across quantiles (with 95% bootstrap confidence bounds (CB) based on a VAR(4) model for IP and NFCI as data-generating process)

E Regressions on industry characteristics

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

	Quantile					OLS
	5%	25%	50%	75%	95%	
Intercept	-0.77*** (0.04)	-0.43*** (0.02)	-0.24*** (0.01)	-0.12*** (0.01)	0.04 (0.04)	-0.31*** (0.02)
Value added	-0.13** (0.06)	-0.07** (0.03)	-0.01 (0.02)	0.05*** (0.02)	0.16*** (0.06)	-0.03 (0.02)
Capital intensity	0.21*** (0.06)	0.13*** (0.04)	0.08*** (0.02)	0.02 (0.02)	-0.12** (0.05)	0.07** (0.02)
Materials intensity	-0.05 (0.05)	-0.04* (0.02)	-0.01 (0.01)	0.01 (0.02)	0.07 (0.05)	-0.01 (0.01)
Energy intensity	-0.02 (0.05)	0.06* (0.03)	0.02 (0.01)	-0.03* (0.02)	-0.02 (0.07)	0.01 (0.02)
Production labor intensity	-0.12* (0.07)	-0.03 (0.04)	0.02 (0.03)	0.05** (0.02)	0.11** (0.05)	-0.01 (0.03)
Overhead labor intensity	0.32*** (0.08)	0.24*** (0.04)	0.12*** (0.03)	-0.01 (0.03)	-0.21*** (0.08)	0.14*** (0.03)
Labor hoarding	0.11* (0.06)	0.09*** (0.03)	0.05*** (0.02)	0.04** (0.02)	-0.01 (0.04)	0.06*** (0.02)
Concentration ratio	-0.11* (0.06)	-0.05 (0.04)	-0.01 (0.03)	0.02 (0.02)	0.11* (0.06)	-0.01 (0.03)
Durability dummy	-0.25*** (0.06)	-0.19*** (0.03)	-0.10*** (0.02)	-0.03** (0.02)	0.04 (0.04)	-0.12*** (0.02)
#observations	74	74	74	74	74	74
R^2	0.54	0.64	0.57	0.38	0.38	0.59

Notes: This table shows the estimated coefficient of the regressions of the NFCI quantile and OLS coefficients on industry characteristics based on the total manufacturing sector for the horizon $h = 3$. The White 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 E.2: Regression of the NFCI quantile and OLS coefficients on industry characteristics based on the durable goods sector (45 industries)

	Quantile					OLS
	5%	25%	50%	75%	95%	
Intercept	-0.96*** (0.04)	-0.55*** (0.02)	-0.31*** (0.02)	-0.17*** (0.01)	0.03 (0.05)	-0.40*** (0.02)
Value added	-0.10 (0.06)	-0.10*** (0.03)	-0.02 (0.02)	0.04** (0.02)	0.18*** (0.06)	-0.04* (0.02)
Capital intensity	-0.08 (0.07)	0.08 (0.05)	0.09*** (0.03)	0.12*** (0.02)	0.27*** (0.09)	0.07*** (0.02)
Materials intensity	-0.23*** (0.05)	-0.11*** (0.03)	-0.05** (0.02)	0.04** (0.02)	0.17*** (0.06)	-0.05** (0.02)
Energy intensity	0.08 (0.05)	0.10** (0.04)	0.03 (0.02)	-0.06*** (0.01)	-0.04 (0.09)	0.03 (0.02)
Production labor intensity	-0.12** (0.05)	0.06 (0.05)	0.07* (0.04)	0.12*** (0.02)	0.29*** (0.07)	0.05 (0.03)
Overhead labor intensity	0.27*** (0.08)	0.32*** (0.05)	0.18*** (0.03)	0.07** (0.03)	0.00 (0.08)	0.20*** (0.03)
Labor hoarding	0.04 (0.03)	0.06*** (0.02)	0.04*** (0.01)	0.04*** (0.01)	0.03 (0.03)	0.04*** (0.01)
Concentration ratio	0.01 (0.04)	-0.02 (0.04)	-0.01 (0.03)	-0.02 (0.02)	-0.05 (0.05)	-0.01 (0.03)
#observations	45	45	45	45	45	45
R^2	0.75	0.75	0.60	0.56	0.58	0.67

Notes: This table shows the estimated coefficient of the regressions of the NFCI quantile and OLS coefficients on industry characteristics based on the durable goods sector for the horizon $h = 3$. The White 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 E.3: Regression of the NFCI quantile and OLS coefficients on industry characteristics based on the nondurable goods sector (29 industries)

	Quantile					OLS
	5%	25%	50%	75%	95%	
Intercept	-0.48*** (0.07)	-0.23*** (0.03)	-0.12*** (0.02)	-0.05*** (0.02)	0.06** (0.02)	-0.17*** (0.02)
Value added	-0.05 (0.07)	0.00 (0.03)	0.01 (0.02)	0.00 (0.02)	0.01 (0.02)	0.00 (0.03)
Capital intensity	0.19* (0.10)	0.10* (0.05)	0.09** (0.04)	0.04 (0.04)	-0.30*** (0.06)	0.05 (0.04)
Materials intensity	0.09 (0.05)	0.01 (0.03)	0.01 (0.02)	-0.02 (0.02)	0.01 (0.02)	0.02 (0.02)
Energy intensity	-0.29*** (0.09)	-0.08** (0.03)	-0.02 (0.02)	0.02 (0.02)	0.06 (0.03)	-0.06** (0.03)
Production labor intensity	-0.13 (0.11)	-0.03 (0.04)	0.02 (0.03)	0.04 (0.03)	0.02 (0.03)	-0.01 (0.04)
Overhead labor intensity	-0.08 (0.10)	-0.04 (0.04)	-0.01 (0.03)	-0.02 (0.03)	-0.05 (0.03)	-0.04 (0.03)
Labor hoarding	0.12 (0.08)	0.09** (0.04)	0.04 (0.03)	0.06* (0.03)	-0.07 (0.04)	0.06* (0.03)
Concentration ratio	-0.21 (0.15)	-0.11 (0.07)	-0.06 (0.05)	-0.02 (0.05)	0.26*** (0.08)	-0.05 (0.06)
#observations	29	29	29	29	29	29
R^2	0.49	0.52	0.37	0.20	0.68	0.39

Notes: This table shows the estimated coefficient of the regressions of the NFCI quantile and OLS coefficients on industry characteristics based on the nondurable goods sector for the horizon $h = 3$. The White 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.

F Results of current IP growth

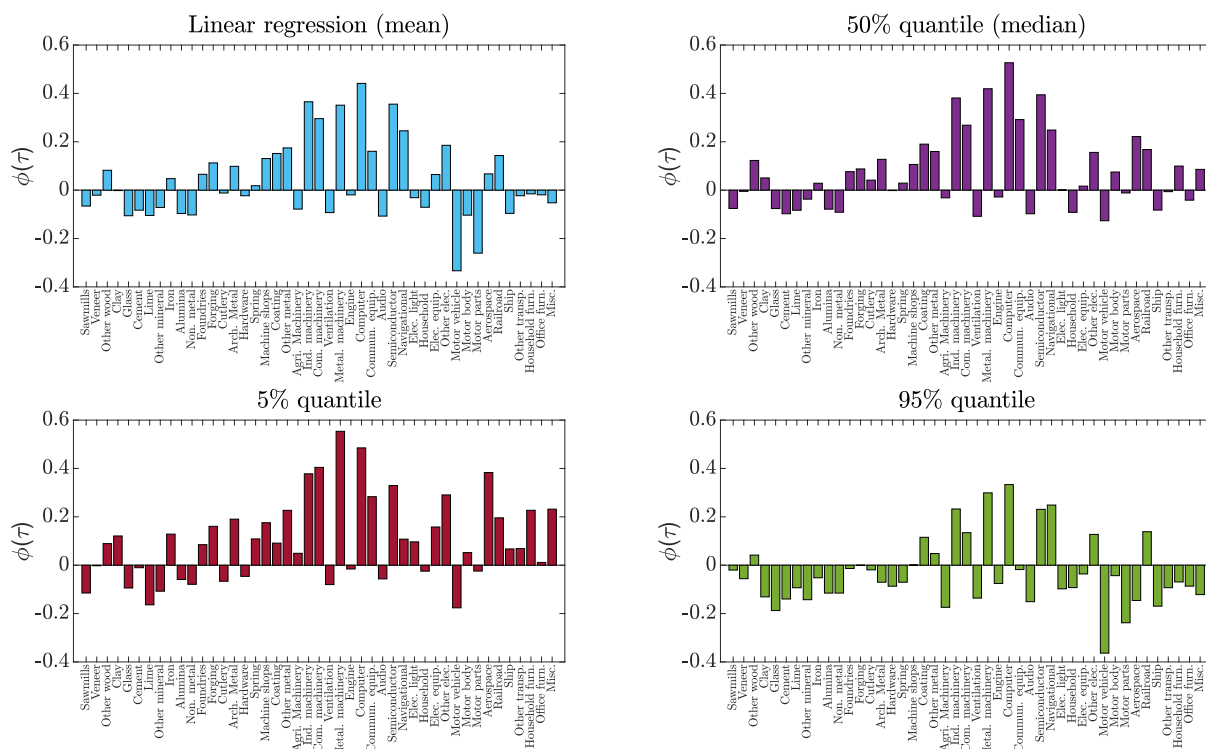


Figure F.1: Estimated linear and quantile regression coefficients of the effect of current IP growth on three-month ahead IP growth ($h = 3$) for the durable goods sector

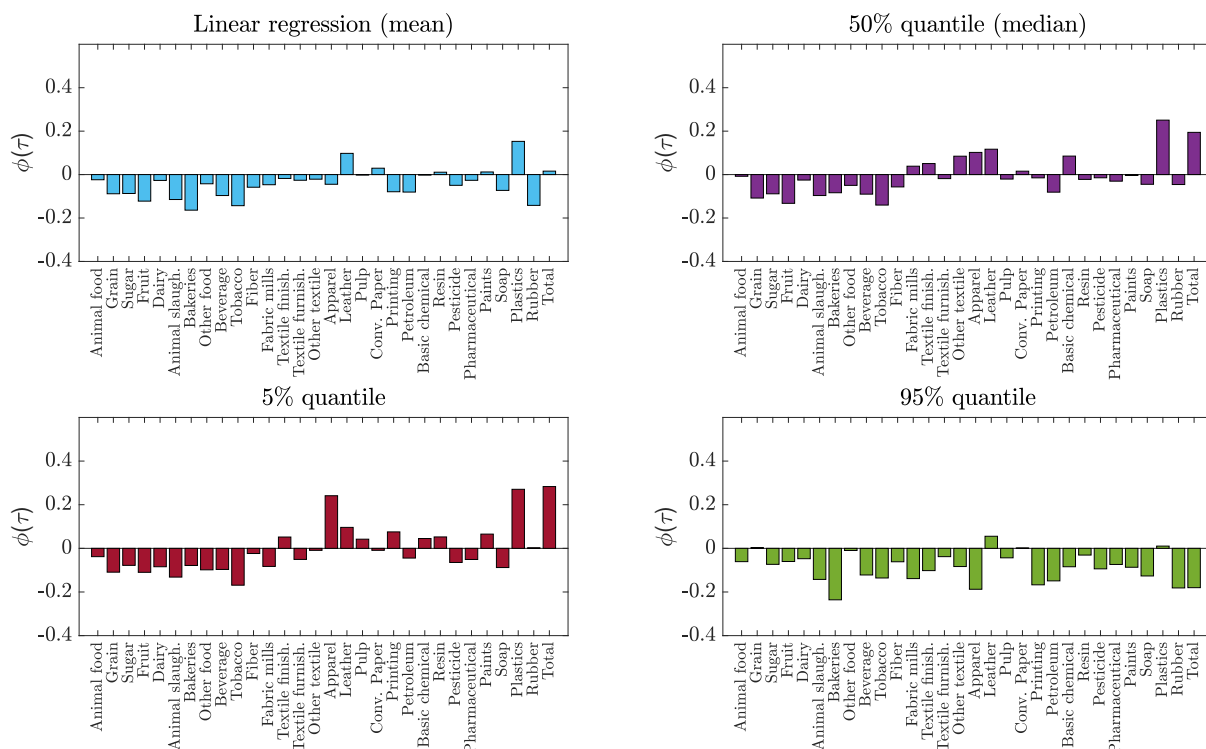


Figure F.2: Estimated linear and quantile regression coefficients of the effect of current IP growth on three-month ahead IP growth ($h = 3$) for the nondurable goods sector

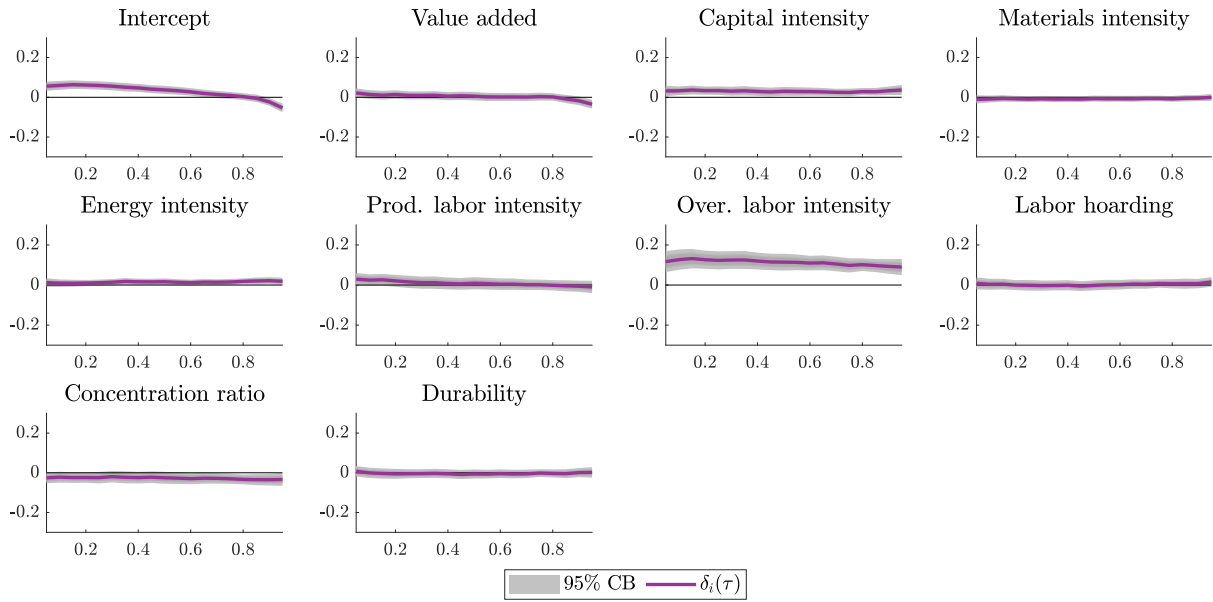


Figure F.3: Estimated industry-characteristic effects on current IP growth quantile coefficients based on $h = 3$ across quantiles for the total manufacturing sector (with 95% confidence bounds (CB) based on White standard errors)

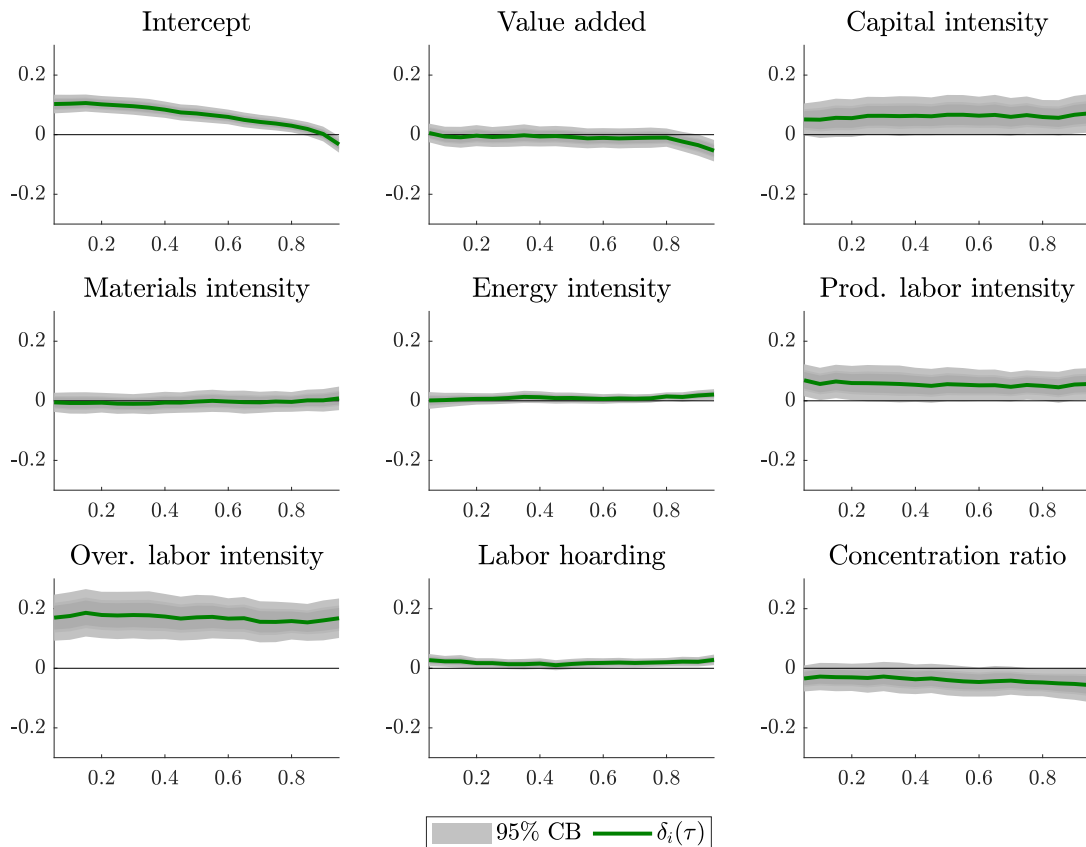


Figure F.4: Estimated industry-characteristic effects on current IP growth quantile coefficients based on $h = 3$ across quantiles for the durable goods sector (with 95% confidence bounds (CB) based on White standard errors)

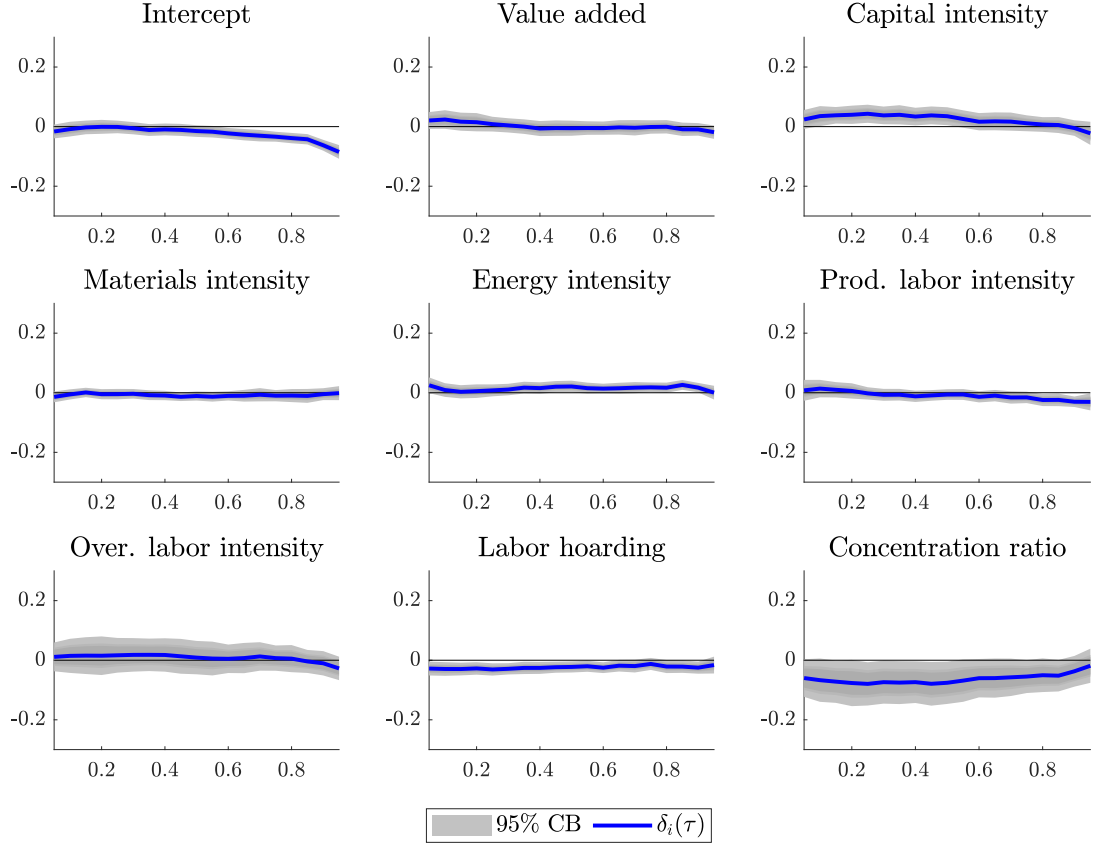


Figure F.5: Estimated industry-characteristic effects on current IP growth quantile coefficients based on $h = 3$ across quantiles for the nondurable goods sector (with 95% confidence bounds (CB) based on White standard errors)

G 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 control 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 τ th quantile of $\bar{y}_{i,t+h}$ conditional on these variables is given by

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

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

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.² We follow Gilchrist and Zakrajšek (2012) and obtain the real federal fund 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.³ The time series are given in Figure G.1.

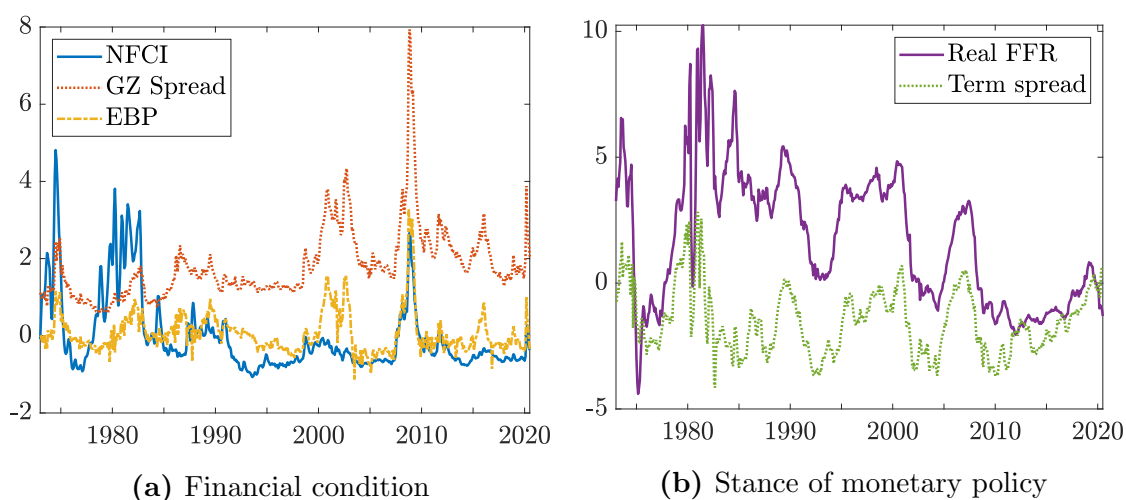


Figure G.1: Time series of U.S. financial condition and the stance of monetary policy over the period January 1973 to July 2020

²<https://fred.stlouisfed.org/>

³<https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html>

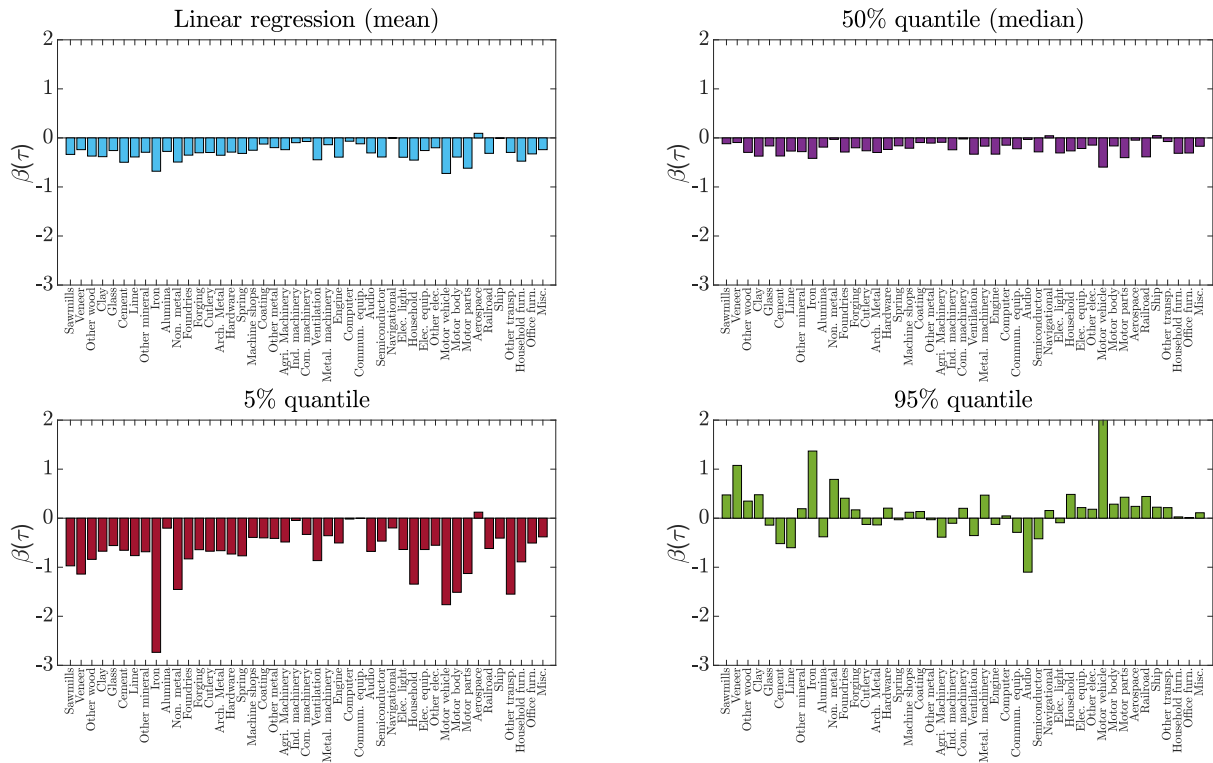


Figure G.2: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) after controlling for GZ variables for the durable goods sector

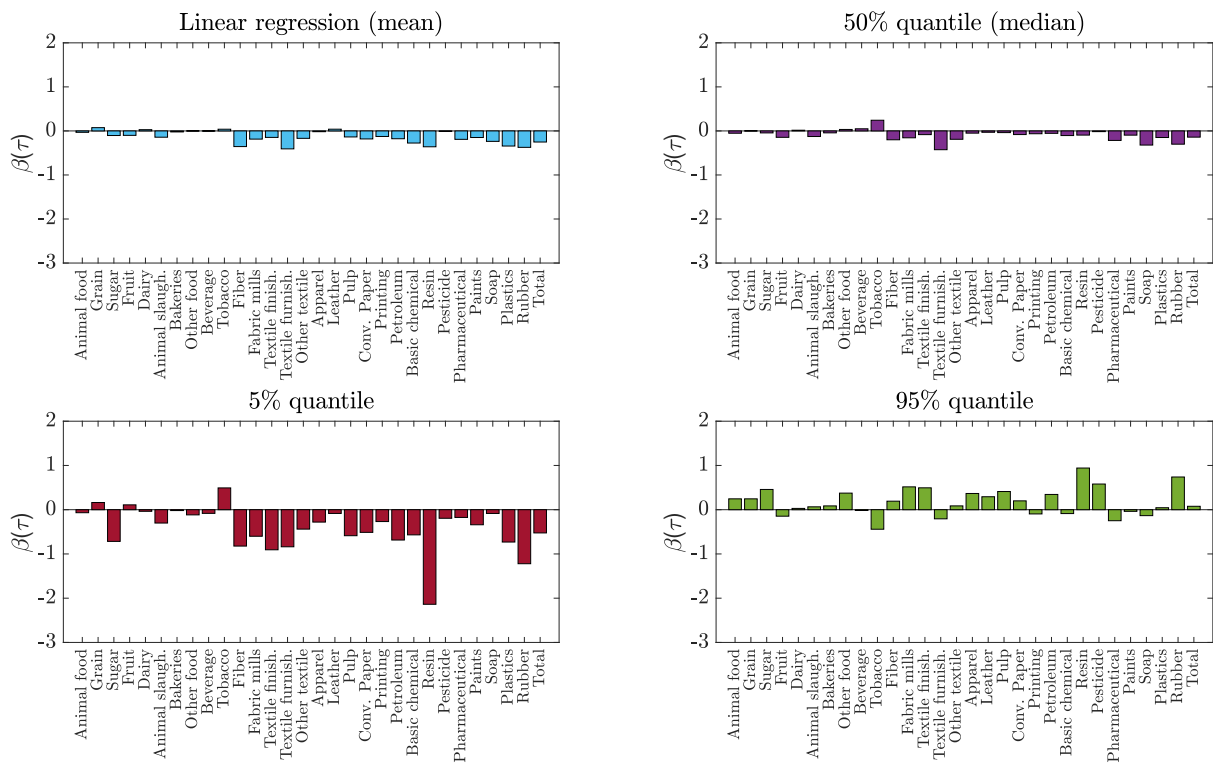


Figure G.3: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) after controlling for GZ variables for the nondurable goods sector

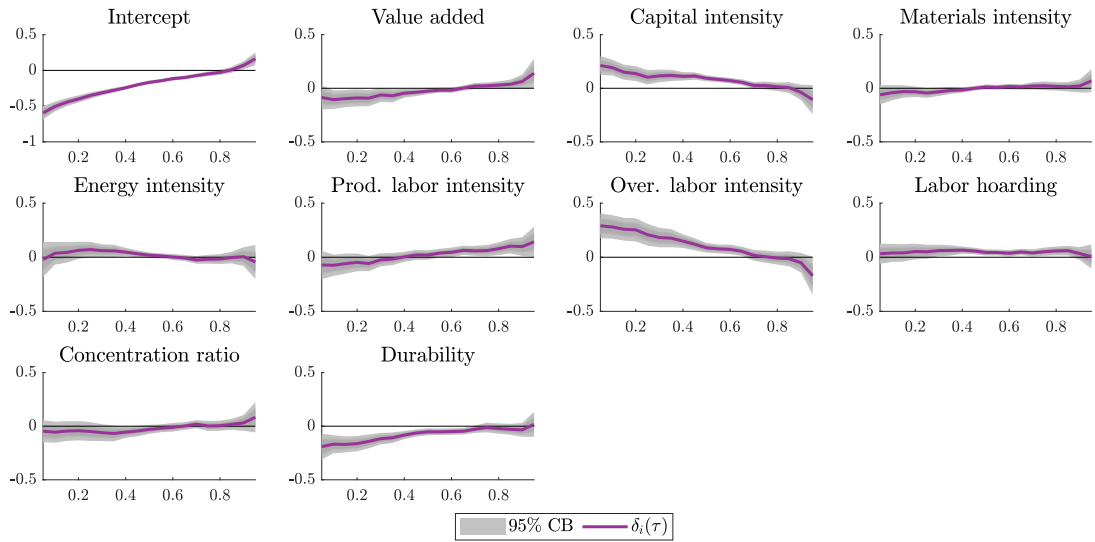


Figure G.4: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for GZ variables based on $h = 3$ across quantiles for the total manufacturing sector (with 95% confidence bounds (CB) based on White standard errors)

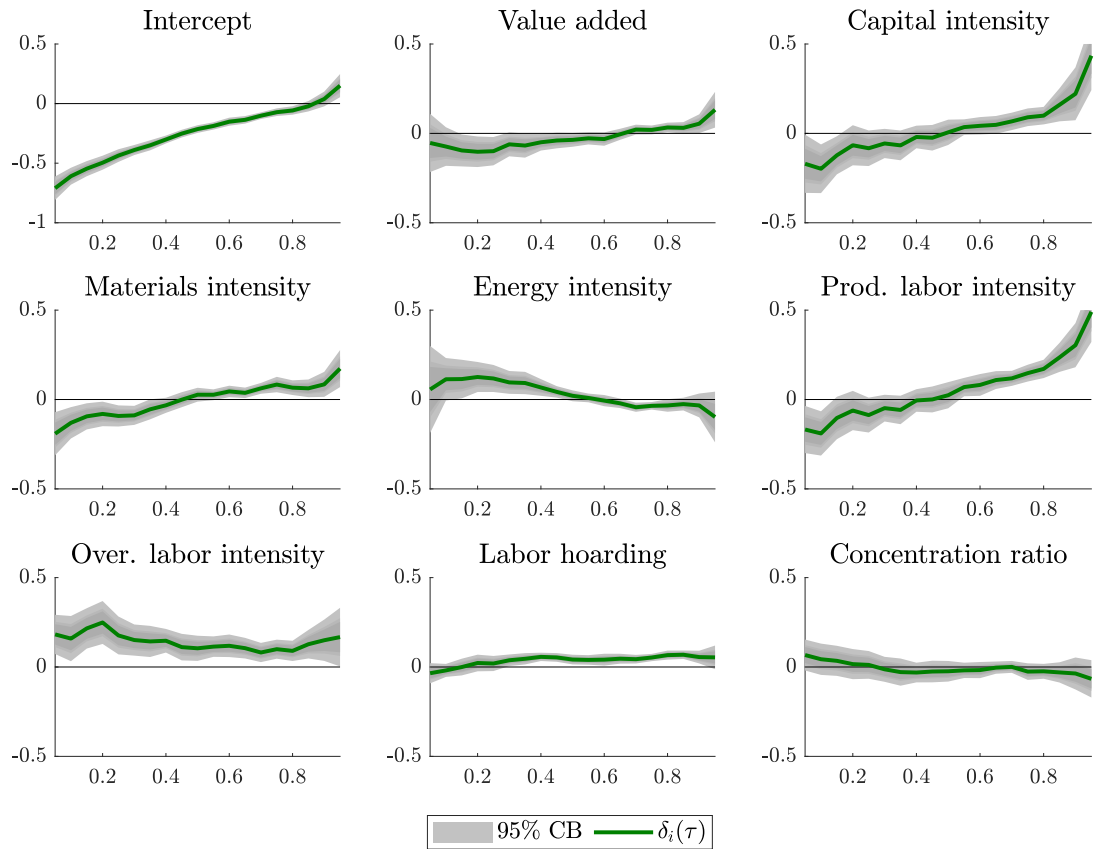


Figure G.5: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for GZ variables based on $h = 3$ across quantiles for the durable goods sector (with 95% confidence bounds (CB) based on White standard errors)

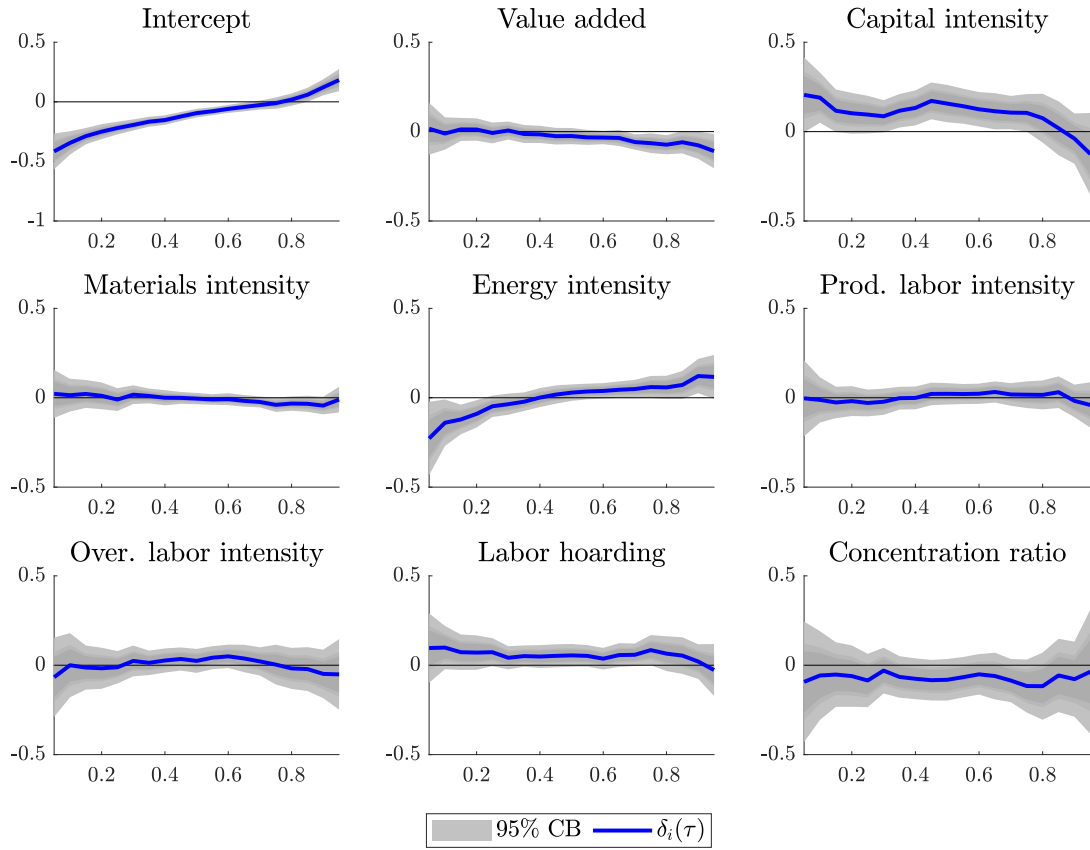


Figure G.6: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for GZ variables based on $h = 3$ across quantiles for the nondurable goods sector (with 95% confidence bounds (CB) based on White standard errors)

H 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 τ th quantile of $\bar{y}_{i,t+h}$ conditional on $\mathbf{x}_{i,t}$ and the latent factor structure is given by

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

for $t = 1, \dots, T - h$ and industries $i = 1, \dots, N$, where $\mathbf{f}_t(\tau)$ 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 $i = 1, \dots, N$ and $\mathbf{f}_t(\tau)$ for $t = 1, \dots, T - h$. 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 factors is optimal.

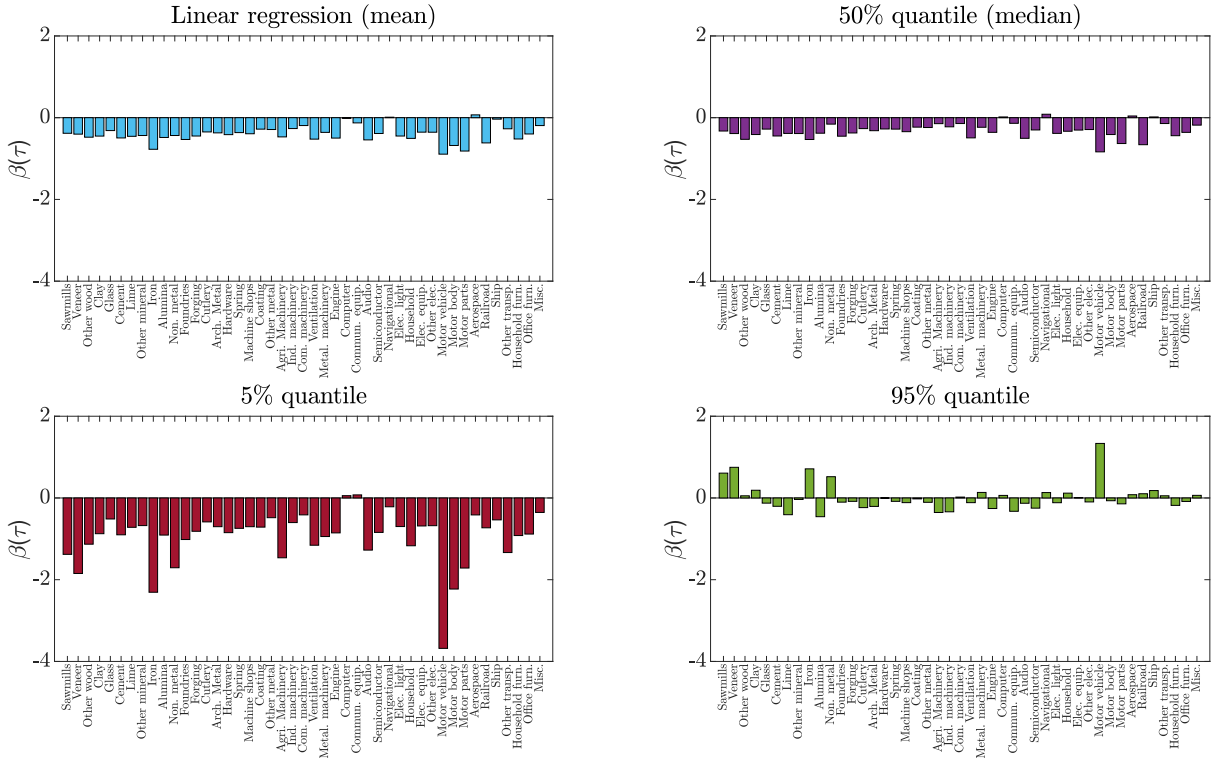


Figure H.1: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) after controlling for unobserved heterogeneity for the durable goods sector

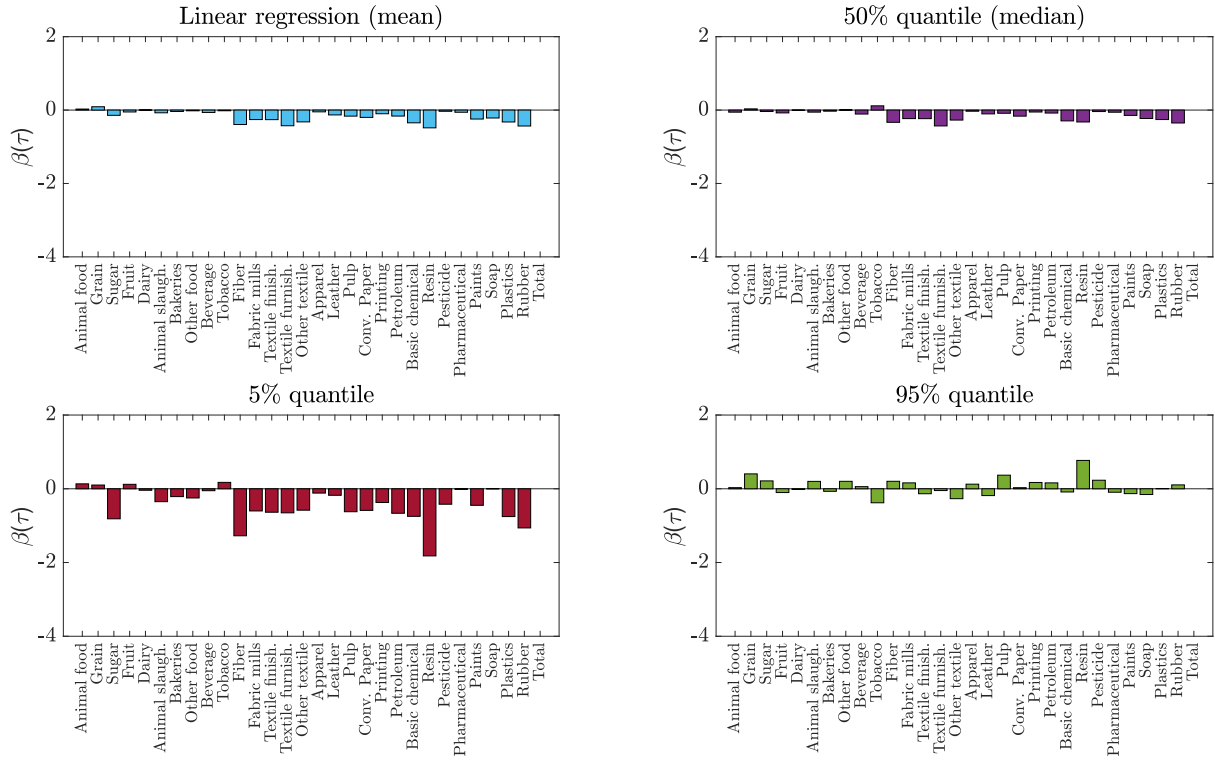


Figure H.2: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) after controlling for unobserved heterogeneity for the nondurable goods sector

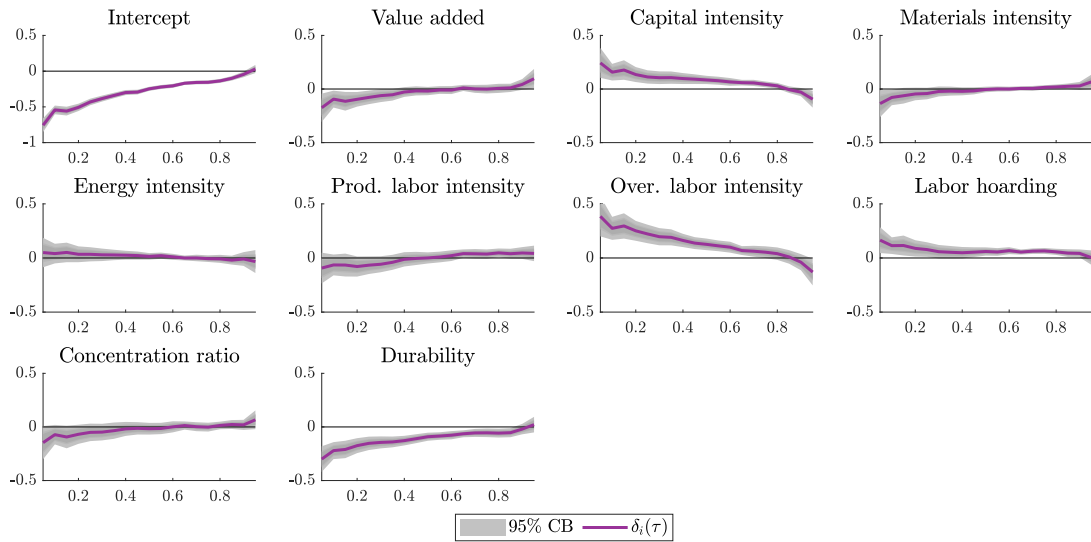


Figure H.3: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for unobserved heterogeneity based on $h = 3$ across quantiles for the total manufacturing sector (with 95% confidence bounds (CB) based on White standard errors)

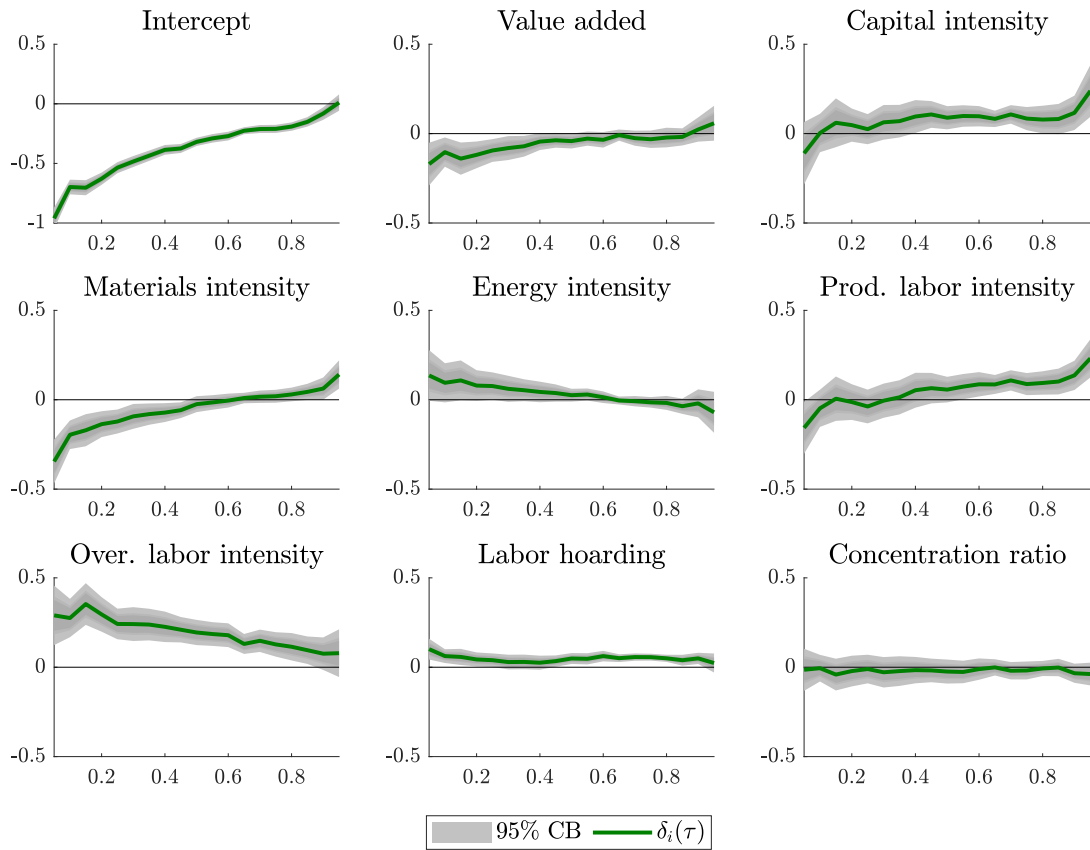


Figure H.4: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for unobserved heterogeneity based on $h = 3$ across quantiles for the durable goods sector (with 95% confidence bounds (CB) based on White standard errors)

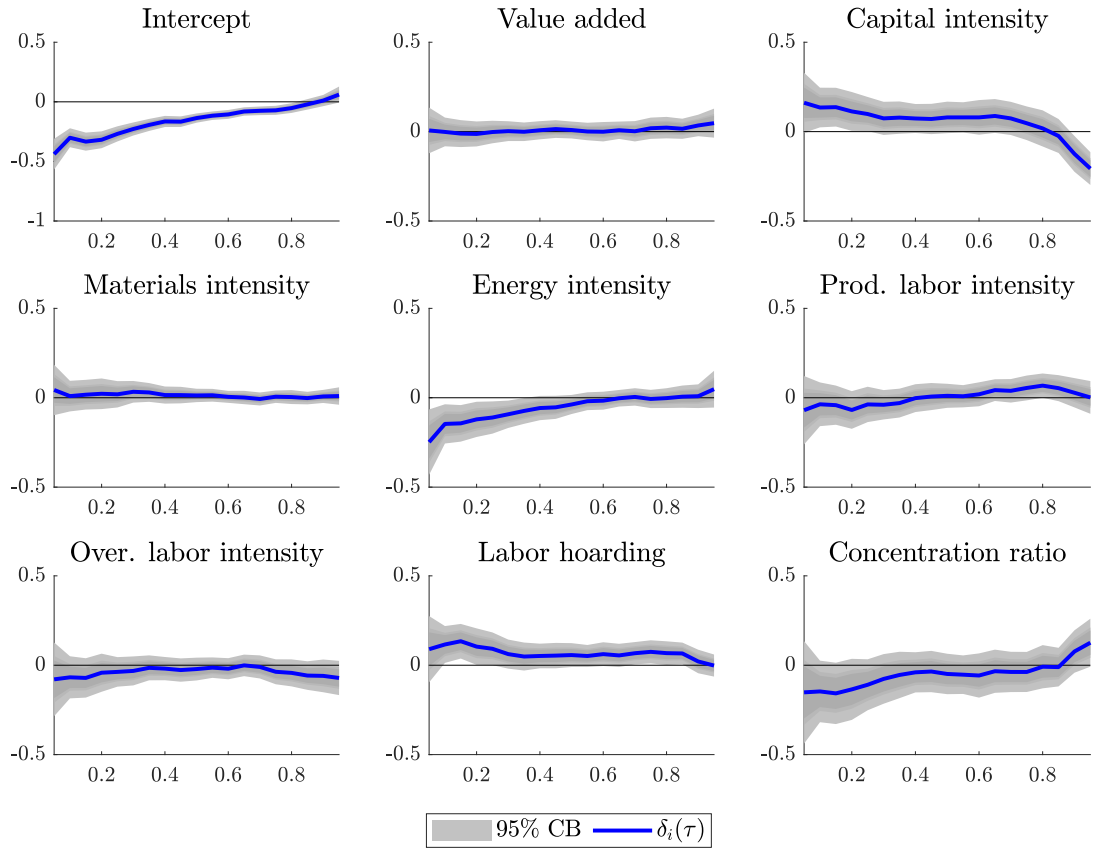


Figure H.5: Estimated industry-characteristic effects on NFCI quantile coefficients after controlling for unobserved heterogeneity on $h = 3$ across quantiles for the nondurable goods sector (with 95% confidence bounds (CB) based on White standard errors)

I Alternative horizons

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

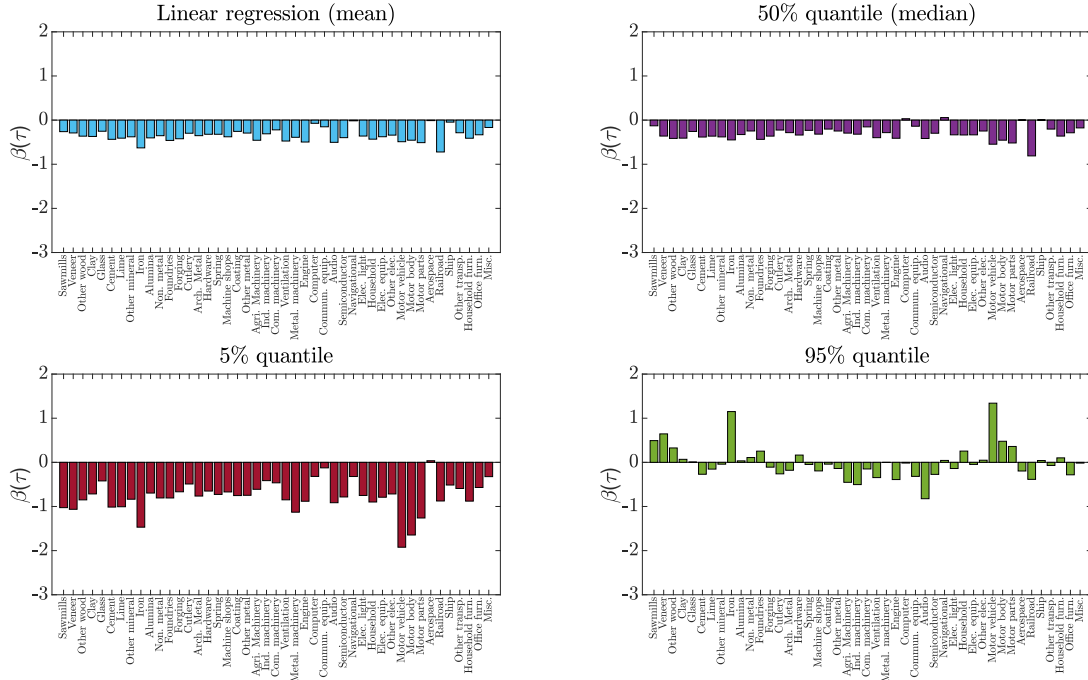


Figure I.1: Estimated linear and quantile regression coefficients of the effect of the NFCI on six-month ahead IP growth ($h = 6$) for the durable goods sector

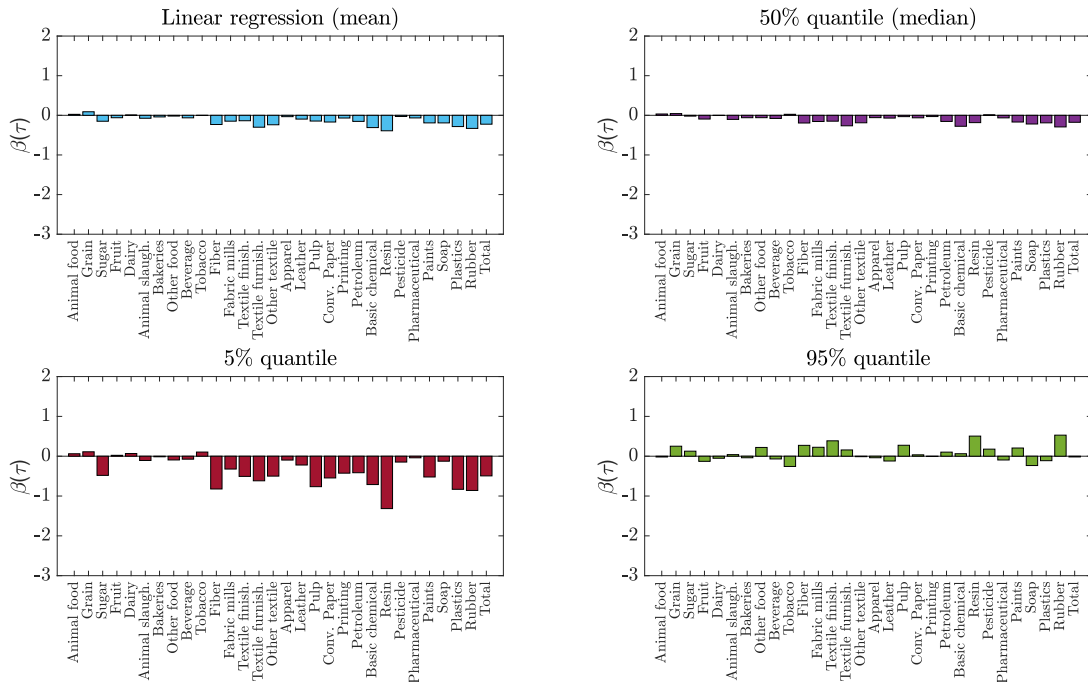


Figure I.2: Estimated linear and quantile regression coefficients of the effect of the NFCI on six-month ahead IP growth ($h = 6$) for the nondurable goods sector

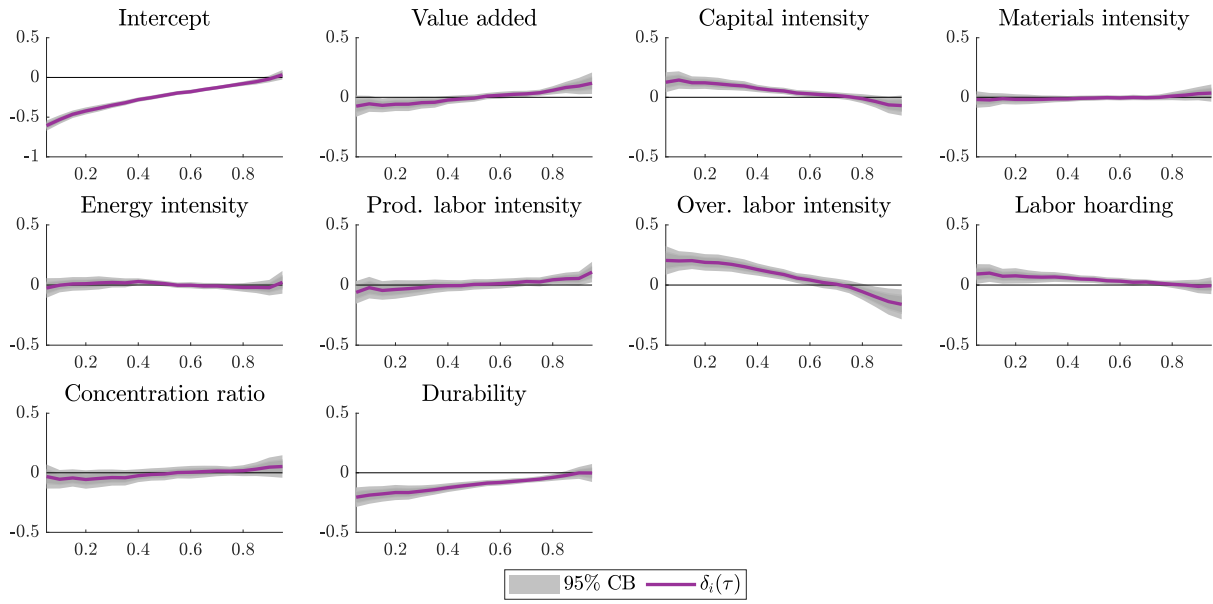


Figure I.3: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 6$ across quantiles for the total manufacturing sector (with 95% confidence bounds (CB) based on White standard errors)

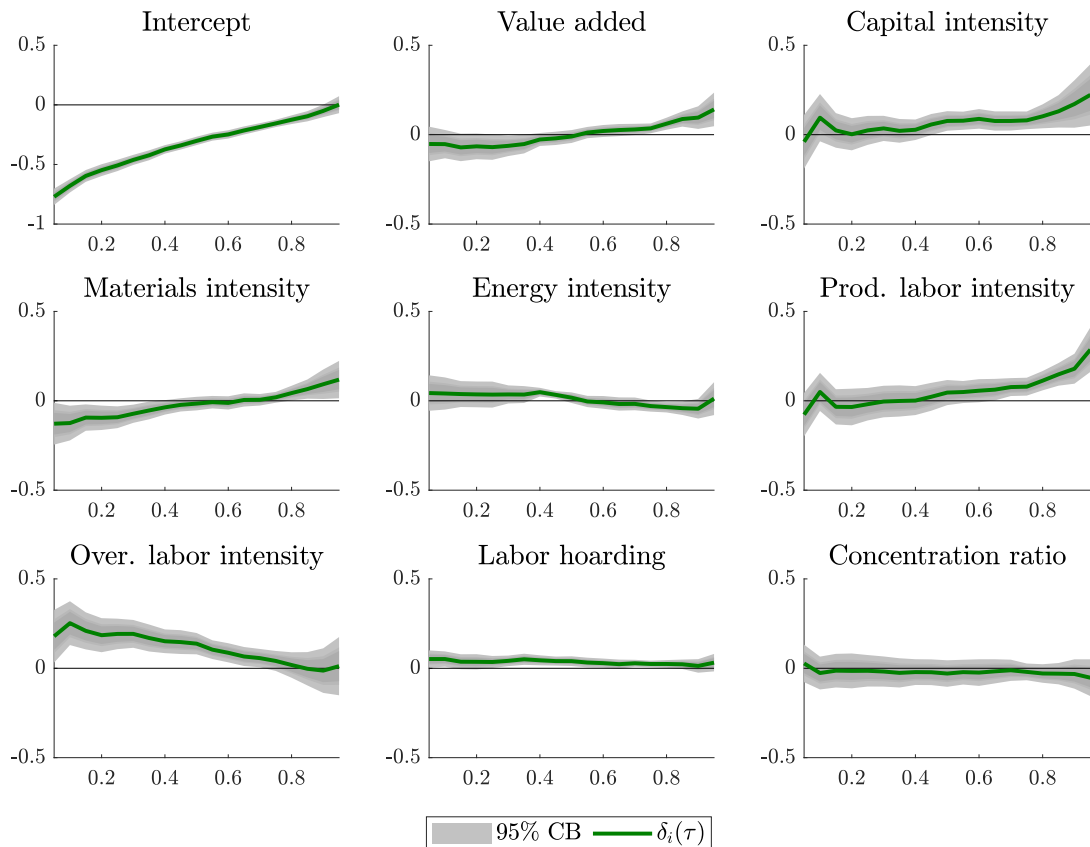


Figure I.4: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 6$ across quantiles for the durable goods sector (with 95% confidence bounds (CB) based on White standard errors)

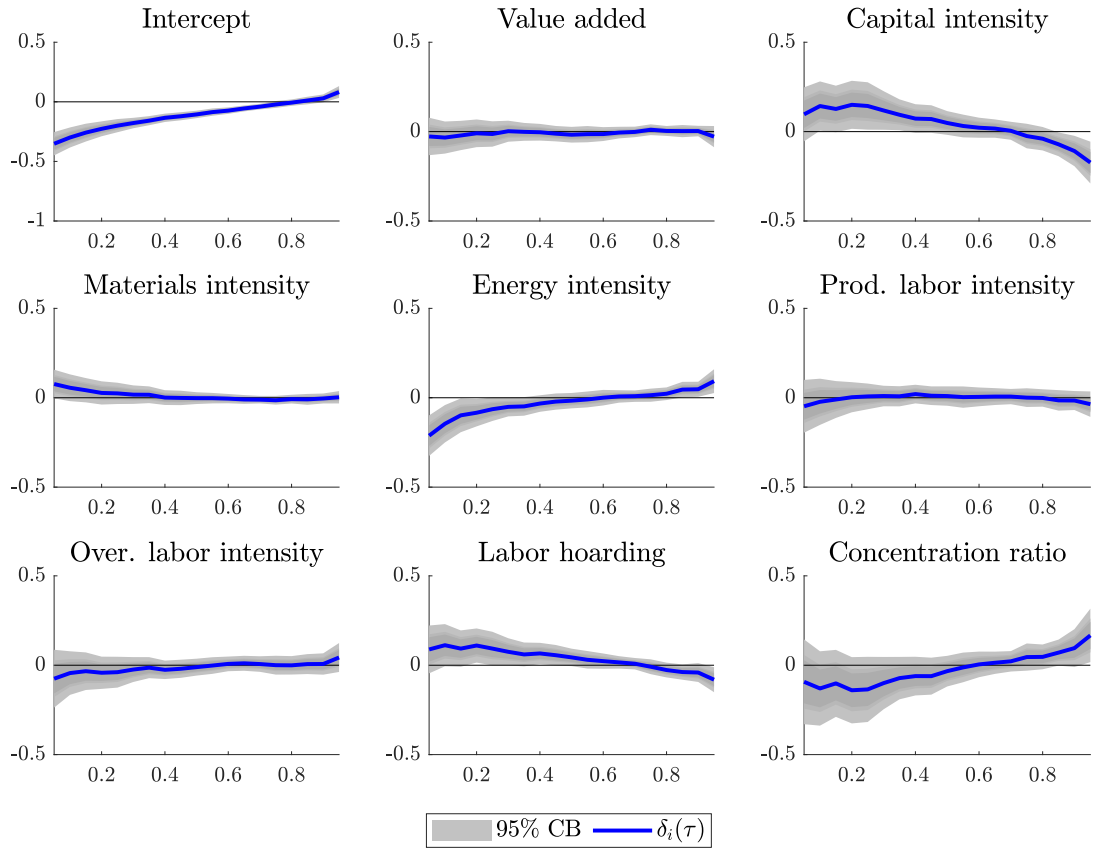


Figure I.5: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 6$ across quantiles for the nondurable goods sector (with 95% confidence bounds (CB) based on White standard errors)

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

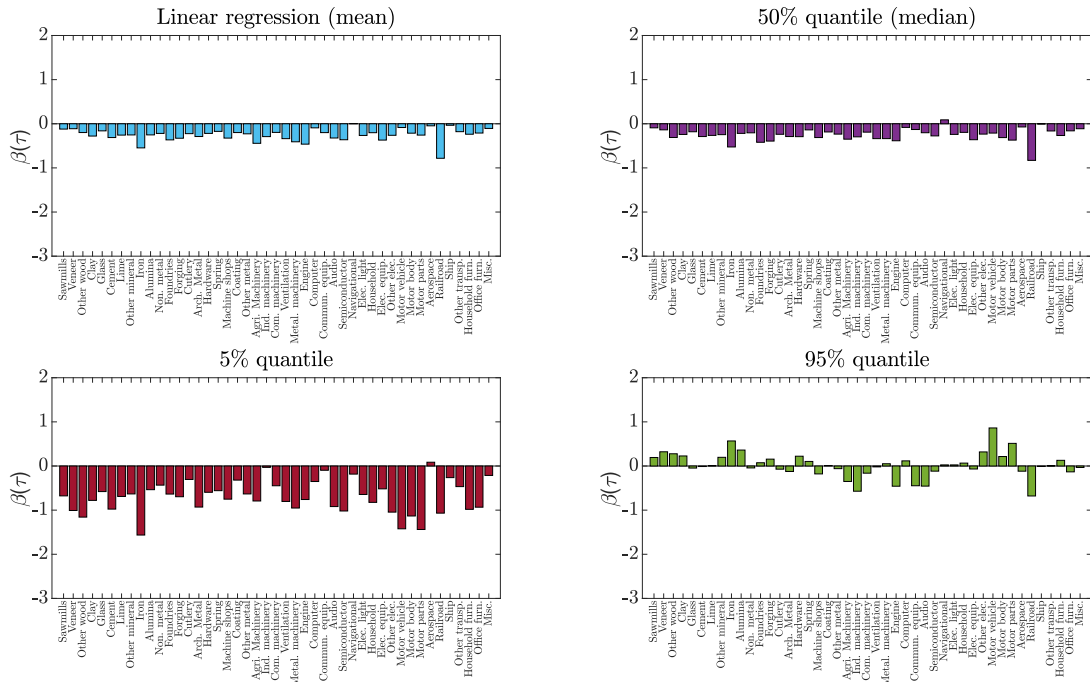


Figure I.6: Estimated linear and quantile regression coefficients of the effect of the NFCI on one year IP growth ($h = 12$) for the durable goods sector

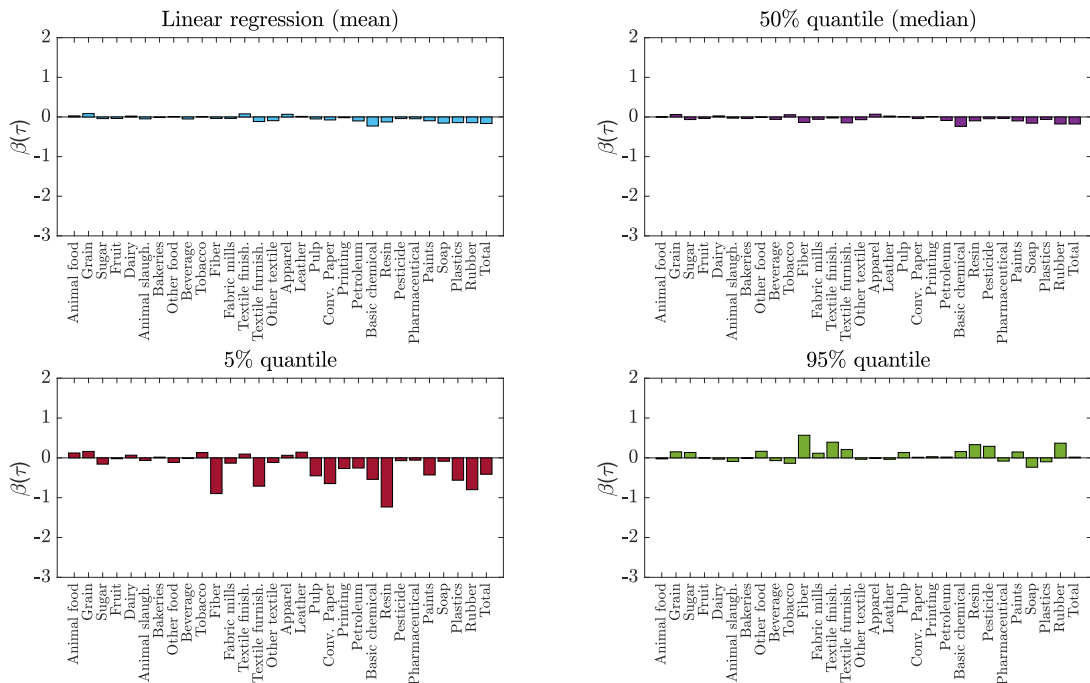


Figure I.7: Estimated linear and quantile regression coefficients of the effect of the NFCI on one year IP growth ($h = 12$) for the nondurable goods sector

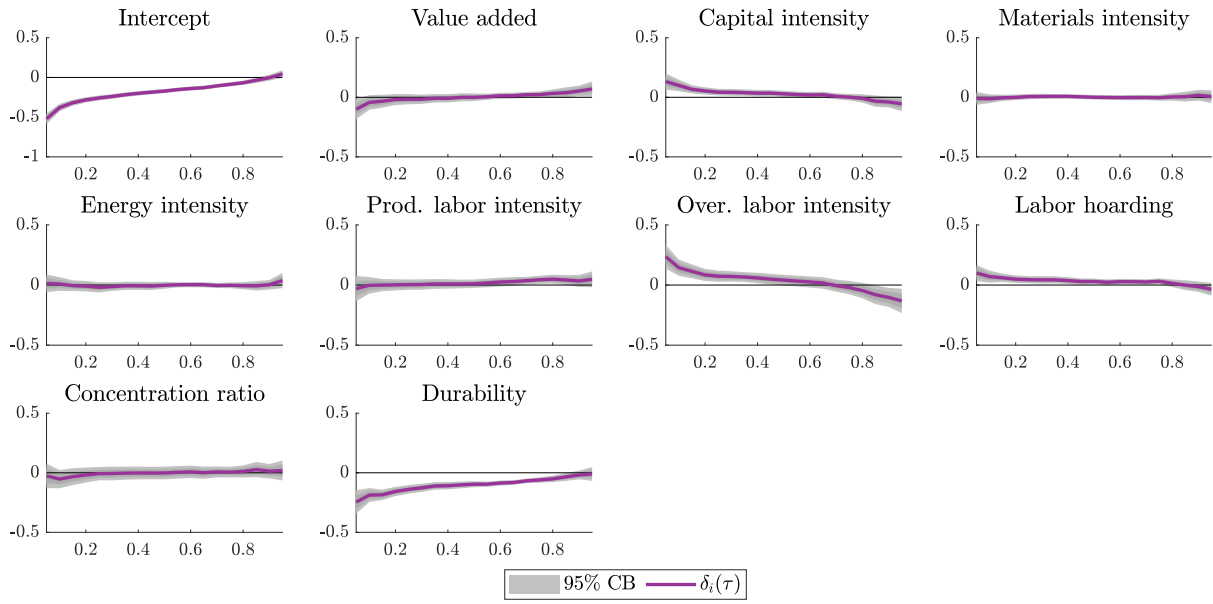


Figure I.8: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 12$ across quantiles for the total manufacturing sector (with 95% confidence bounds (CB) based on White standard errors)

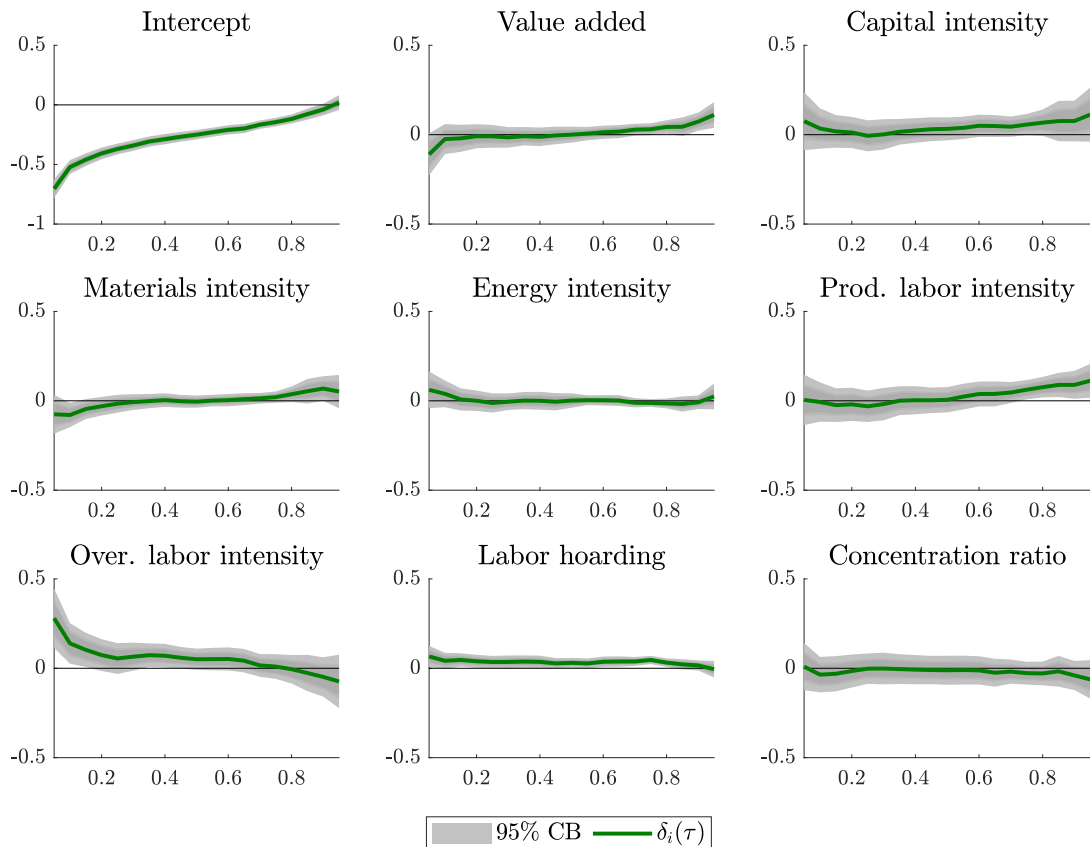


Figure I.9: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 12$ across quantiles for the durable goods sector (with 95% confidence bounds (CB) based on White standard errors)

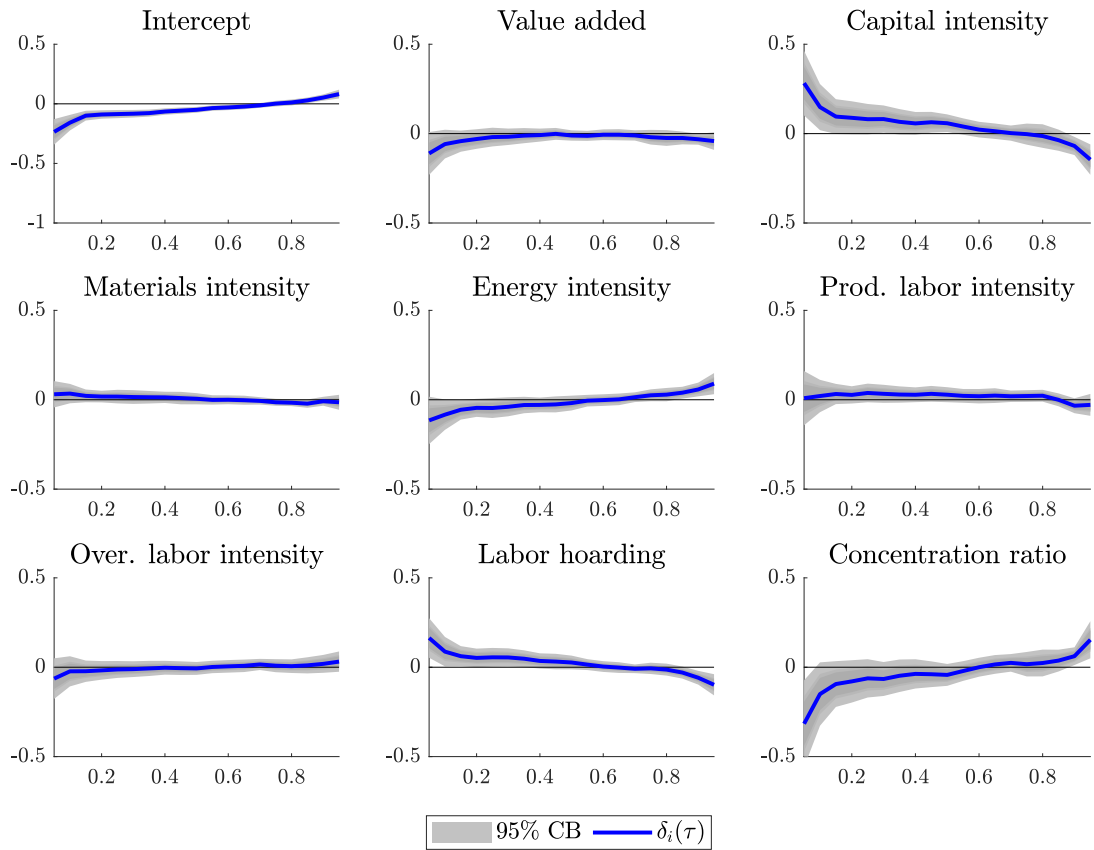


Figure I.10: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 12$ across quantiles for the nondurable goods sector (with 95% confidence bounds (CB) based on White standard errors)

J Alternative NAICS disaggregation levels

J.1 Three-digit NAICS level

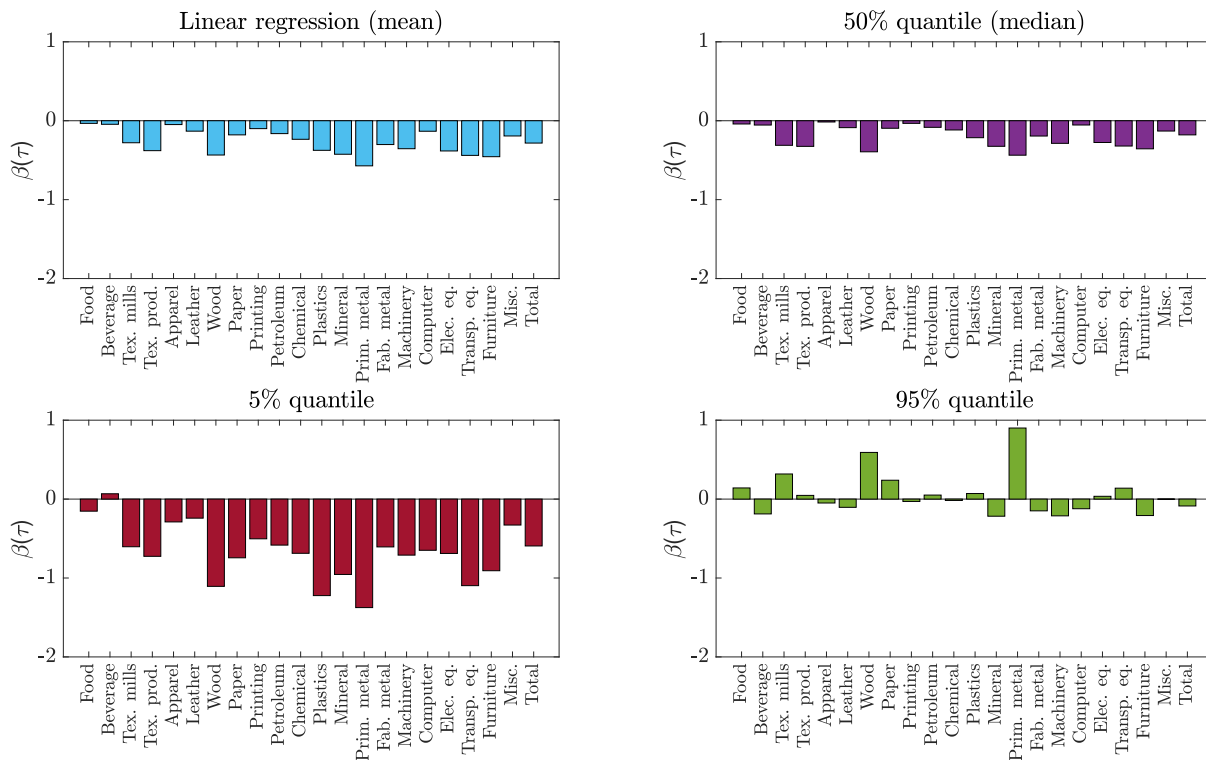


Figure J.1: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for the total manufacturing sector at the three-digit NAICS level

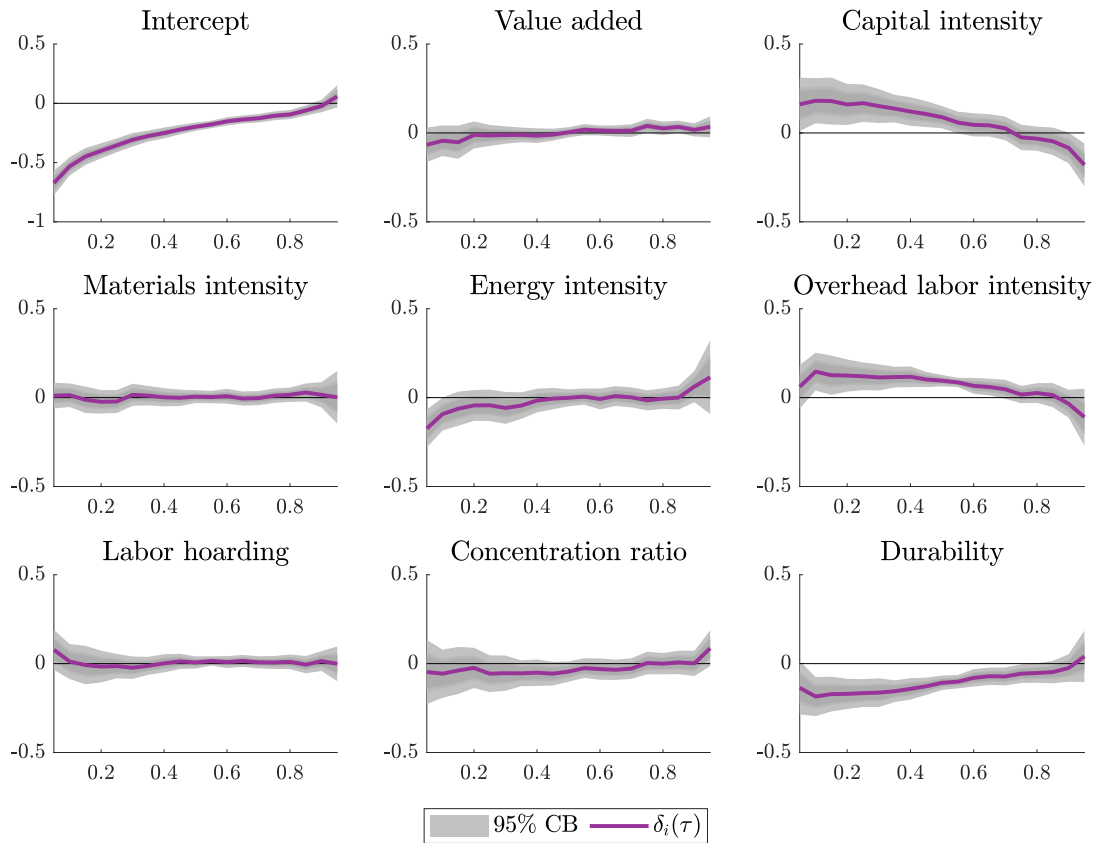


Figure J.2: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the total manufacturing sector at the three-digit NAICS level (with 95% confidence bounds (CB) based on White standard errors)

J.2 Six-digit NAICS level

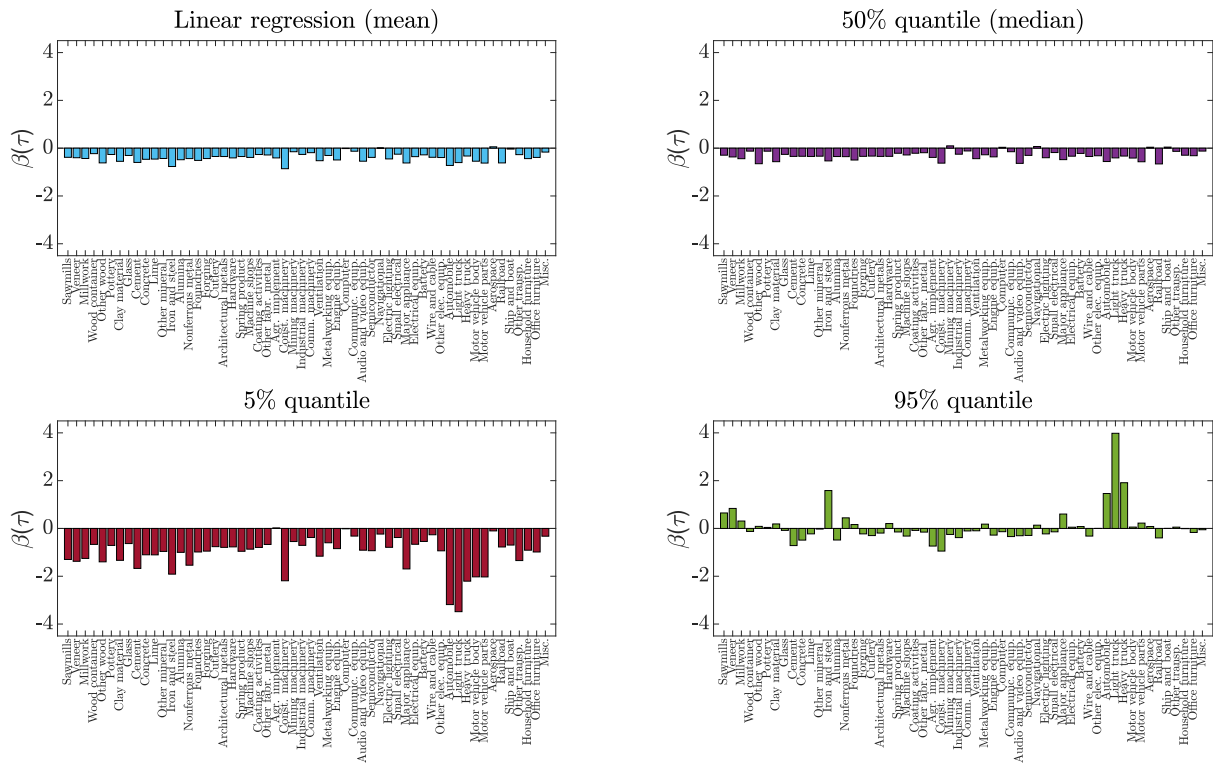


Figure J.3: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for the durable goods sector at the six-digit NAICS level

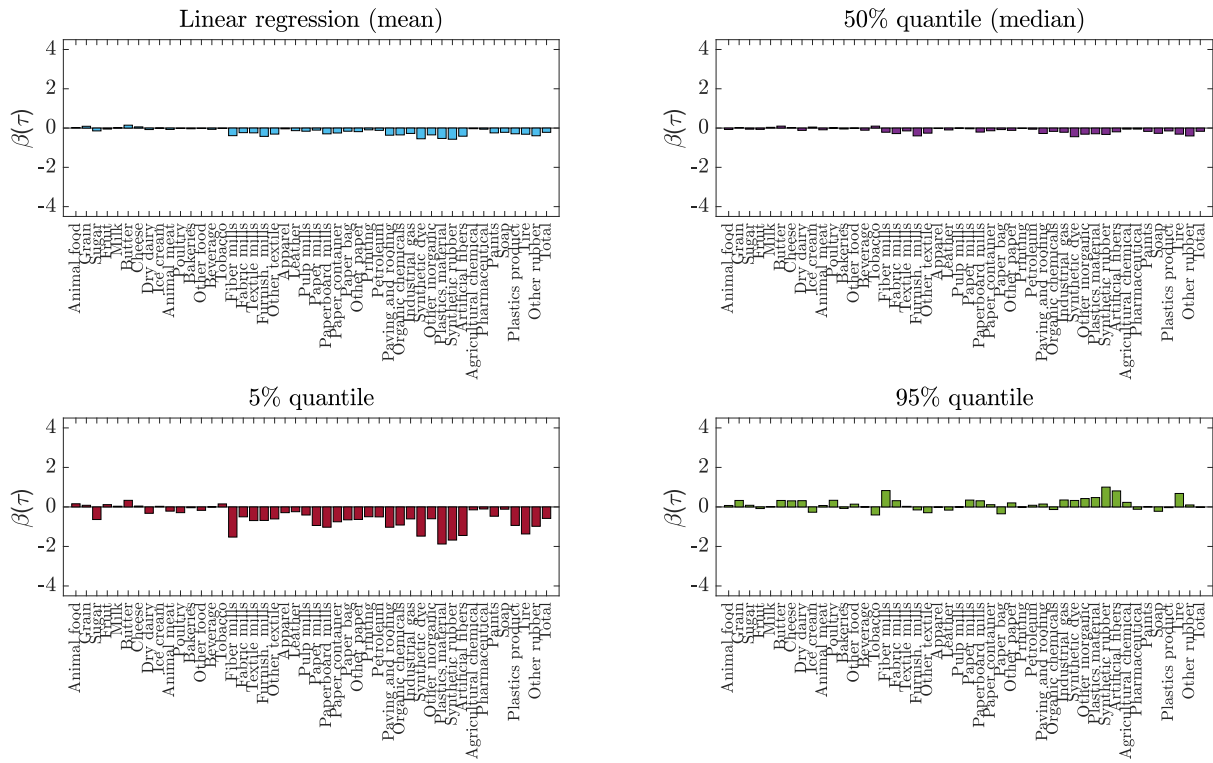


Figure J.4: Estimated linear and quantile regression coefficients of the effect of the NFCI on three-month ahead IP growth ($h = 3$) for the nondurable goods sector at the six-digit NAICS level

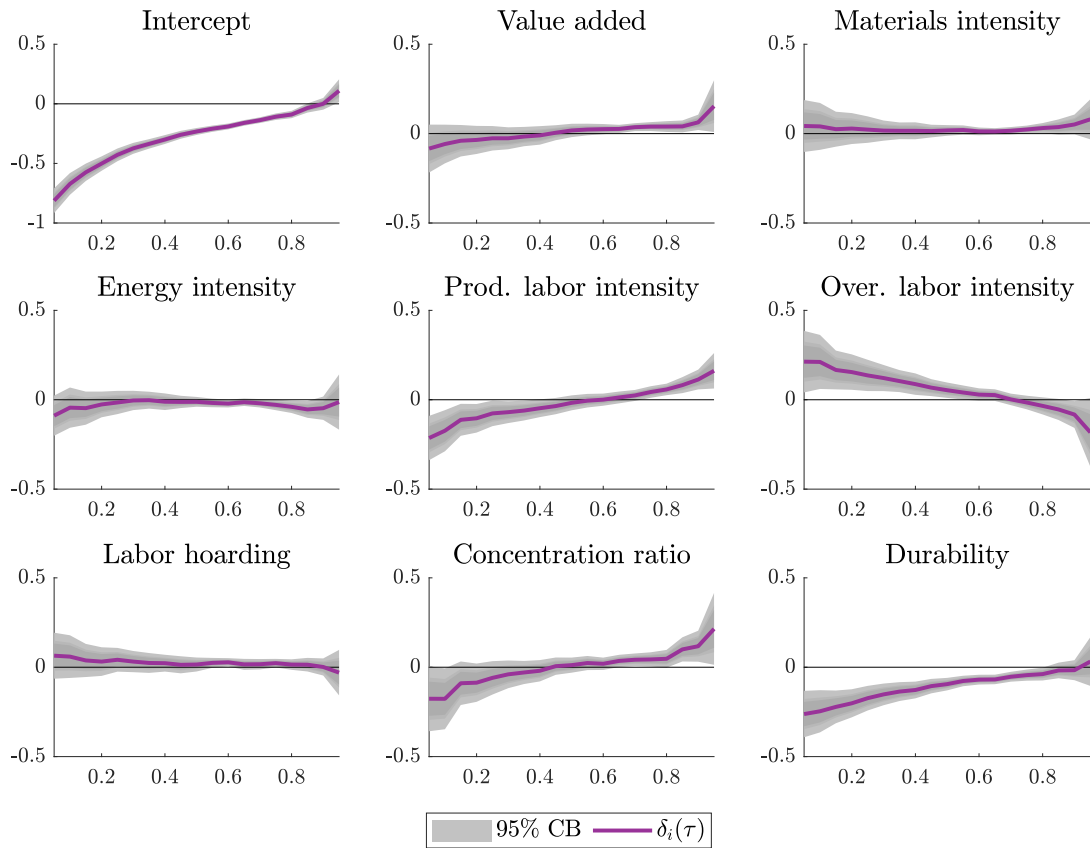


Figure J.5: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the total manufacturing sector at the six-digit NAICS level (with 95% confidence bounds (CB) based on White standard errors)

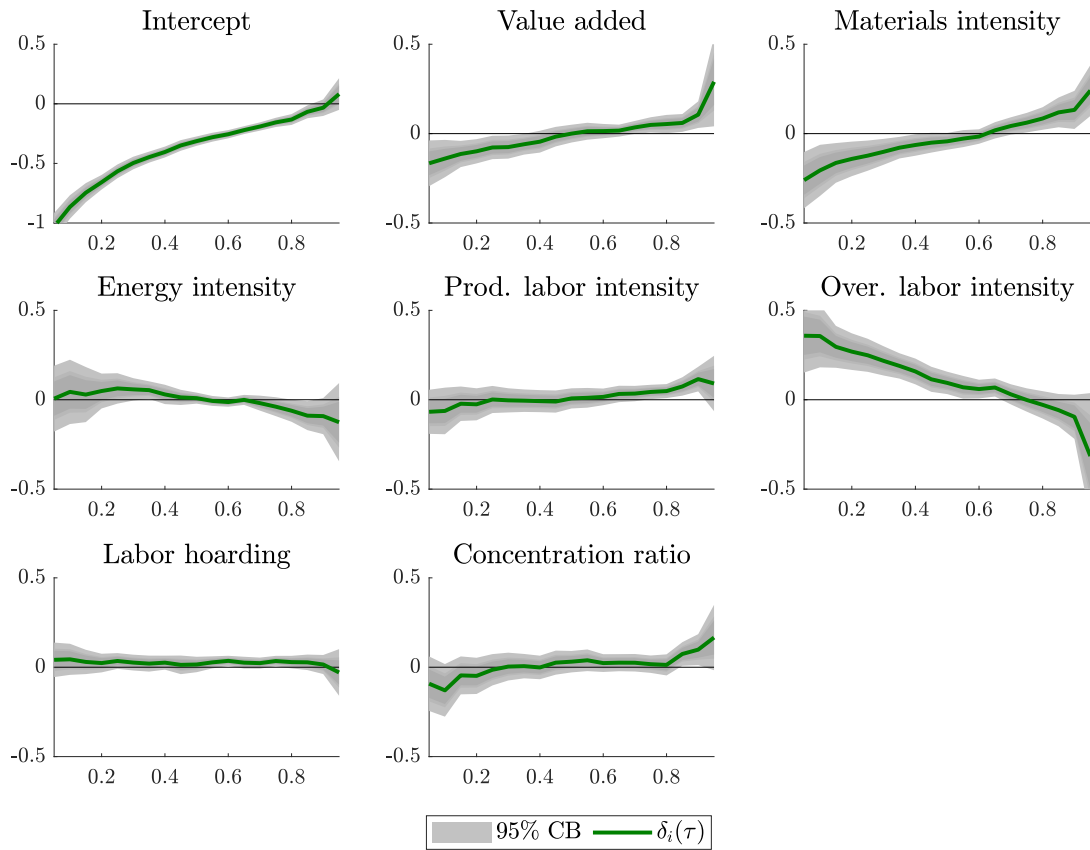


Figure J.6: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the durable goods sector at the six-digit NAICS level (with 95% confidence bounds (CB) based on White standard errors)

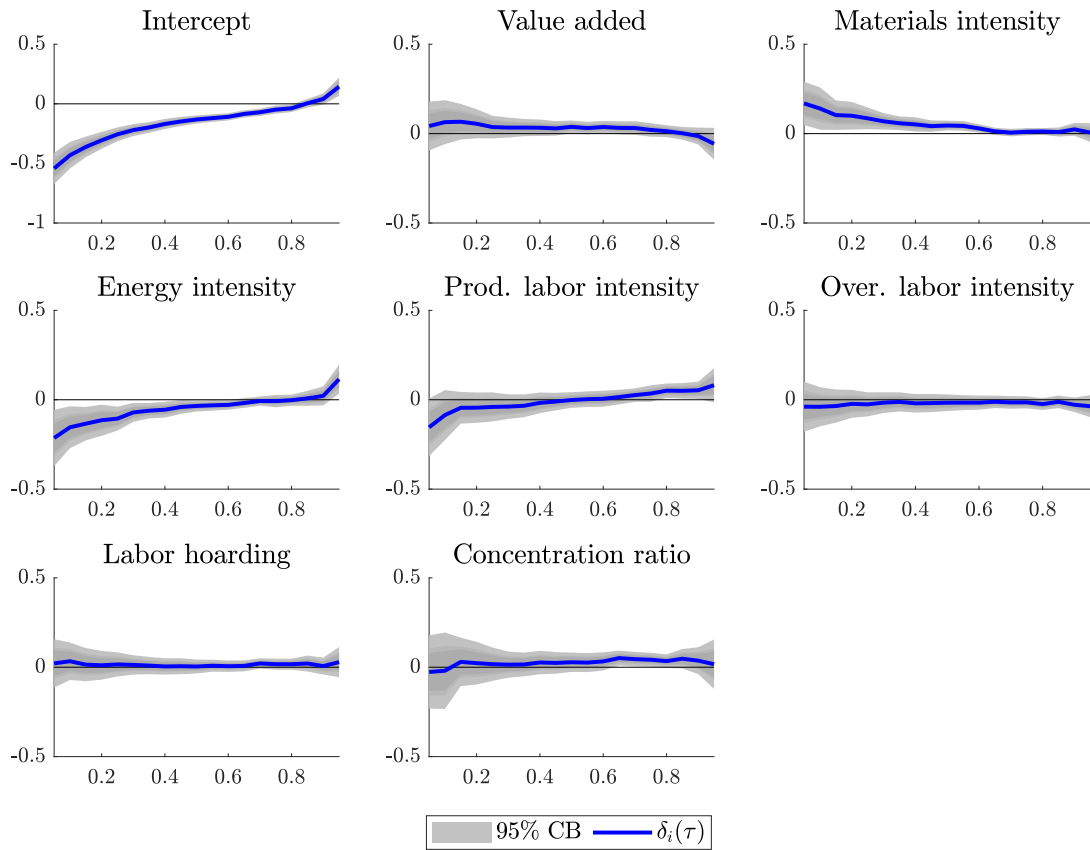


Figure J.7: Estimated industry-characteristic effects on NFCI quantile coefficients based on $h = 3$ across quantiles for the nondurable goods sector at the six-digit NAICS level (with 95% confidence bounds (CB) based on White standard errors)

References

- ADRIAN, T., N. BOYARCHENKO, AND D. GIANNONE (2019): “Vulnerable Growth,” *American Economic Review*, 109, 1263–1289.
- ANDO, T. AND J. BAI (2020): “Quantile Co-Movement in Financial Markets: A Panel Quantile Model With Unobserved Heterogeneity,” *Journal of the American Statistical Association*, 115, 266–279.
- ANDREWS, D. W. K. (1991): “Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation,” *Econometrica*, 59, 817–858.
- BOFINGER, E. (1975): “Estimation of a Density Function Using Order Statistics,” *Australian Journal of Statistics*, 17, 1–7.
- GALVAO, A. F., T. JUHL, G. MONTES-ROJAS, AND J. OLMO (2018): “Testing Slope Homogeneity in Quantile Regression Panel Data with an Application to the Cross-Section of Stock Returns,” *Journal of Financial Econometrics*, 16, 211–243.
- GALVAO, A. F. AND K. KATO (2016): “Smoothed quantile regression for panel data,” *Journal of Econometrics*, 193, 92–112.
- GALVAO, A. F. AND L. WANG (2015): “Efficient minimum distance estimator for quantile regression fixed effects panel data,” *Journal of Multivariate Analysis*, 133, 1–26.
- GILCHRIST, S. AND E. ZAKRAJŠEK (2012): “Credit Spreads and Business Cycle Fluctuations,” *American Economic Review*, 102, 1692–1720.
- HALL, P. AND S. J. SHEATHER (1988): “On the Distribution of a Studentized Quantile,” *Journal of the Royal Statistical Society. Series B (Methodological)*, 50, 381–391.
- KATO, K. (2012): “Asymptotic normality of Powell’s kernel estimator,” *Annals of the Institute of Statistical Mathematics*, 64, 255–273.
- MANSFIELD, E. R. AND B. P. HELMS (1982): “Detecting Multicollinearity,” *The American Statistician*, 36, 158–160.
- YOON, J. AND A. F. GALVAO (2020): “Cluster robust covariance matrix estimation in panel quantile regression with individual fixed effects,” *Quantitative Economics*, 11, 579–608.