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Economic and Policy Uncertainties and Firm Value in the U.S. Consumer Nondurable Goods Industry

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Abstract

This paper examines the impact of macroeconomic and policy-related uncertainties on firm value, measured by Tobin's Q, for a panel of nine major U.S. consumer nondurable goods firms from 1980 through the first quarter of 2022. Utilizing panel quantile regression and panel MIDAS-VAR models, the analysis incorporates firm-level financial variables such as the current and quick ratios, debt-to-asset ratio, and operating income after depreciation. The findings reveal that economic policy uncertainty, consumer confidence, and inflationary expectations are positively associated with Tobin's Q and Granger cause firm value across the distribution. In contrast, recessionary expectations do not significantly influence Tobin's Q, reflecting the essential nature of the sector's products and its relative insulation from business cycle downturns. These results suggest that firms in this sector may benefit from strategic focus on liquidity management, operational efficiency, and responsiveness to shifts in consumer sentiment and policy conditions.

JEL classification: L6, M0, M2.

Keywords: Tobin's Q, Uncertainty, Economic Policy Uncertainty, Inflation expectations, Consumer confidence index, Panel quantile regression, Panel MIDS Vector autoregressive.

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1. Introduction

Nondurable consumer goods are a cornerstone of the U.S. economy, with a substantial share of the GDP and a pivotal role in economic stability and growth. Their consistent demand provides a buffer against economic downturns, supports widespread employment, and serves as a key indicator of economic health. Understanding the dynamics of nondurable goods spending is crucial for policymakers and economists aiming to foster a resilient and prosperous economy.

Nondurable consumer goods encompass a wide range of products such as food, beverages, clothing, fuel, and household items. These goods are typically consumed quickly, necessitating frequent repurchase, which sustains continuous economic activity and contributes substantially to the GDP.

Nondurable consumer goods account for a significant portion of consumer spending, which itself constitutes about 70 percent of the U.S. GDP. According to the U.S. Bureau of Economic Analysis (BEA), nondurable goods represented approximately 21 percent of total personal consumption expenditures in recent years. This category's contribution to GDP highlights its importance in driving economic growth, given that consumption is the largest component of GDP.

The steady demand for nondurable goods provides a stabilizing effect on the economy. Unlike durable goods, which may see fluctuations in demand based on economic cycles, nondurable goods maintain relatively constant demand even during economic downturns. This consistent demand helps buffer the economy against more severe recessions by ensuring ongoing production and employment in sectors related to nondurable goods.

The production and distribution of nondurable goods are critical to various industries, including agriculture, manufacturing, retail, and logistics. These industries collectively employ millions of Americans. For example, the food and beverage industry alone employs a significant portion of the workforce, from agricultural workers to retail employees. This employment is crucial not only for economic stability but also for supporting local economies and communities.

Consumer spending on nondurable goods is a key indicator of economic health. High spending levels typically signal consumer confidence and economic stability. Conversely, a decline in spending on these goods can indicate economic distress or a decrease in disposable income. Policymakers and economists closely monitor these spending patterns to gauge the overall economic climate and to make informed decisions regarding fiscal and monetary policy.

Nondurable goods are often subject to price sensitivity and inflation. Changes in the prices of these goods can significantly impact overall inflation rates, as measured by the Consumer Price Index (CPI). For instance, fluctuations in fuel prices can lead to changes in transportation costs, which then affect the prices of other nondurable goods. Monitoring these price changes helps policymakers address inflationary pressures and maintain economic stability.

Macroeconomic uncertainty is an unavoidable aspect of all economies and can have notable implications for firms in the consumer nondurable goods sector. Companies in this industry frequently face the challenge of making strategic financial and operational decisions in the face of unpredictable economic conditions. The connection between uncertainty and firm behavior is well established in economic theory. Foundational work, such as Sandmo (1971), explored how uncertainty shapes corporate decision-making, while John Kenneth Galbraith's The Age of Uncertainty (1977) emphasized its broad implications for financial and economic systems.

Expanding on these theoretical insights, subsequent research by Flacco and Kroetch (1986), Fooladi (1986), Fooladi and Kayhani (1991), and Adrangi and Raffiee (1999) examined how firms adjust their strategies to cope with market risks. These studies demonstrated that in uncertain environments, firms tend to modify their production plans, pricing behavior, and approaches to profit maximization. Advances in the measurement of uncertainty—particularly those developed by Becker et al. (2012, 2014, 2016), Davis et al. (2013), and Golchin and Riahi (2021)—have made it possible to more precisely evaluate the effects of both economic and policy-related uncertainty on firm performance across sectors.

Recent empirical studies have applied these refined measures to a variety of markets. For example, Adrangi et al. (2023a, 2023b; 2024a, 2024b, 2024c; 2025a, 2025b) have investigated how uncertainty affects financial markets, the airline industry, and crude oil markets in the United States. Building on this evolving literature, the present study shifts focus to the consumer nondurable goods sector, offering a new perspective on how firms in this essential industry respond to evolving macroeconomic and policy-driven uncertainties.

The remainder of the paper is organized as follows. Section II offers a review of literature pertaining to Tobin's Q. The data and sources of the sample data are discussed in section III. A brief description of the econometric methodology is the subject of section IV. Section V is earmarked for the discussion of the empirical findings. Summary, conclusions, and implications of the findings for money managers and firms comprise the last section.

2. Literature review

This section establishes the conceptual foundation of Tobin's Q and examines scholarly work investigating variables that affect corporate Q ratios, with particular attention to economic policy fluctuations and market uncertainty across different sectors and geographical contexts pertinent to our investigation. Given that much of the research has focused predominantly on petroleum and natural gas companies—presumably due to data accessibility and the straightforward nature of Q calculations in this sector—we maintain a focused approach to our literature survey.

Tobin's Q represents a valuation metric that compares a company's market capitalization to the cost of recreating its asset base:

Q = Corporate market valuation / Asset replacement expenditure

Where corporate market valuation equals equity market capitalization plus debt market value, and asset replacement expenditure represents the current cost to duplicate the company's asset portfolio.

The interpretation of Q ratios follows three primary scenarios. When Q exceeds 1.0, market participants value the enterprise above its asset replacement cost, suggesting robust future growth potential or possible market overvaluation. When Q falls below 1.0, the market assigns lower value than asset replacement costs, indicating potential undervaluation or suboptimal asset utilization. When Q approximates 1.0, market valuation aligns closely with replacement costs, suggesting appropriate pricing.

Corporate decision-makers and financial analysts extensively utilize Q ratios for strategic planning. Elevated Q values typically motivate capital investment in new assets and may identify attractive takeover candidates. Furthermore, the metric captures market sentiment regarding anticipated profitability and operational effectiveness.

Tobin's Q serves as a fundamental tool across corporate finance, macroeconomic analysis, and industrial economics for evaluating investment patterns and market effectiveness. The following discussion presents major research contributions across diverse economic sectors and identifies supplementary studies relevant to our investigation.

Butt et al. (2023) evaluate Q's effectiveness as a performance indicator, with particular emphasis on marketing research applications. While acknowledging the metric's popularity among researchers due to its predictive characteristics and cross-industry applicability, the authors express reservations about its dependability, especially in studies examining intangible resources such as marketing initiatives, human capital, and research and development investments. Using data from 196 Pakistani publicly-listed non-financial corporations across multiple industries over a five-year timeframe, sourced from financial reports and equity pricing data, the researchers empirically evaluate Q's appropriateness by benchmarking it against stock returns as an alternative performance measure. The study concludes that although Tobin's Q maintains its value as a dependable metric, researchers should exercise prudence when applying it to studies involving intangible assets. The authors suggest that marketing researchers explore alternative measures like stock returns or employ multiple performance indicators to ensure analytical robustness.

Jin and Jorion (2006) examine how derivative-based risk management affects the market valuation of American petroleum and gas enterprises. The theoretical foundation suggests that financial risk mitigation through hedging strategies should enhance corporate value by stabilizing earnings volatility and reducing costs related to financial difficulties, taxation, and insufficient investment. Analyzing 119 U.S. oil and gas producers from 1998-2001 (totaling 330 firm-year observations), the researchers gathered comprehensive data from annual 10-K filings, including detailed hedging activity information covering futures contracts, options, swaps, and fixed-price physical delivery agreements. Despite demonstrating hedging's effectiveness in reducing stock price volatility, the study finds no corresponding improvement in Q ratios. This finding contradicts conventional wisdom that risk management necessarily enhances firm value, suggesting the benefits may be more complex and depend on industry-specific characteristics or the particular risks being managed.

Fadul (2005) explores connections between ethical conduct, corporate social responsibility, and firm valuation within the petroleum industry. Based on 55 U.S. oil and gas extraction companies, the research employs multiple social indices—environmental stewardship, workforce diversity, community engagement, and ethical practices—as CSR performance proxies. Firm value assessment utilizes Return on Equity and an approximated Q ratio. Multiple regression analysis demonstrates that ethical behavior correlates positively and significantly with firm value. Notably, the diversity index shows positive correlation with Q-measured firm value in the equipment and services subsector.

Syaifulhaq and Herwany (2020) investigate the connection between corporate capital structure, particularly debt composition, and overall enterprise value. Motivated by ongoing corporate finance debates regarding optimal capital structure for value maximization, the study emphasizes understanding how various financial structures influence firm performance, especially in capital-intensive sectors like oil and gas. Employing quantitative methodology with statistical analysis tools, the research examines relationships between debt ratios (as percentage of total capital) and firm value through metrics including Q and Return on Equity. Results reveal intricate relationships between capital structure and firm value. Findings suggest that moderate debt levels can boost firm value through tax advantages and profitability leverage, while excessive debt negatively impacts firm value and Q due to heightened financial distress risk. These results support the Trade-Off Theory, which proposes an optimal debt level balancing benefits against costs.

Yildiz and Kapusuzoglu (2020) investigate hedging activities' effects on oil and gas firm performance, specifically examining whether these practices create value. Researchers utilize panel regression models to explore relationships between firm value (proxied by Q) and various hedging measures, including derivative usage. Data encompasses 76 exploration, production, and integrated oil and gas companies actively using hedging instruments and reporting these activities in financial statements from 2007-2016, sourced from the IHS Markit database. Findings reveal that hedging activities generally negatively impact firm value and Q. This consistent result across models suggests that extensive hedging may signal financial distress or poor management to investors. The study also finds that highly leveraged firms engage more in hedging without necessarily improving firm value, and smaller firms or those facing financial distress use derivatives more aggressively. The study concludes that while hedging aims to manage risk, it does not consistently enhance firm value and its Q. Additional researchers including Phan et al. (2014) and Danielsen (2017) also investigate relationships between hedging activities, renewable energy, and firm valuation using Q in the oil and gas sector.

García-Gómez et al. (2022) analyze economic policy uncertainty's impact on U.S. tourism industry performance using 296 tourism companies from 2000-2018, creating 3,068 firm-year observations. Panel regression analysis using system-generalized method of moments reveals that economic policy uncertainty negatively affects return on assets, return on equity, and Tobin's Q. Results remain consistent across different variable specifications, with firm size and leverage moderating the relationship between economic policy uncertainty and firm performance. Panel quantile regression estimation shows asymmetric associations, with firms in the 25th percentile of ROA and ROE less affected by uncertainty, while firms in the 75th percentile and above of Tobin's Q distribution remain unaffected by economic policy uncertainty.

Demir and Ersan (2017) investigate Economic Policy Uncertainty's effect on cash holding decisions in BRIC countries. Using firm-level data from 2006-2015, researchers find that companies prefer holding more cash during uncertain periods after controlling for firm-level variables with industry and year fixed effects. Results prove robust across alternative control variables, uncertainty calculations, and sub-sample

selections. Both country-specific and global economic policy uncertainty significantly positively impact corporate cash holdings.
Current literature demonstrates substantial academic interest in examining firm valuation through Tobin's Q and its relationships with management decisions, risk management activities, and economic policy or market uncertainties. However, a significant research gap exists in analyzing economic and policy uncertainties' impact on Tobin's Q across diverse sectors, particularly the U.S. consumer non-durable goods industry. This study aims to address this critical gap and enhance understanding of these dynamics in this critical sector.

3. Data

Our empirical analysis utilizes financial information extracted from the Compustat database through WRDS, encompassing nine corporations within the durable goods sector across a timeframe extending from 1980's first quarter through 2022's fourth quarter. The complete roster of examined firms appears in Table 1.

Table 1: List of companies examined

The list of the sample companies	Industry	Capitalization	Year	beta
Avon Products	Cosmetics	N/A	1886	N/A
Church & Dwight Inc(CHD)	Household products, e.g., soap, detergent and sanitation	23.52B	1846	0.51
Clorox Co (CLX)	The Health and Wellness, cleaning and disinfecting products, dressings, dips, seasonings, and sauces	15.30B	1913	0.53
International Cosmetics & Perfumes	Luxury fragrances in the Americas, Personal Products	Privately owned 1996	1996	N/A
Colgate-Palmolive Co	Oral, Personal and Home Care; and Pet Nutrition.	71.44B	1806	0.38
Procter & Gamble Co	Beauty; Grooming; Health, Home and Family Care	357.96B	1837	0.43
Scott's Liquid Gold	Personal Products	Private	1954	N/A
Stepan Co	specialty and intermediate chemicals for cleaning, disinfecting	1.28B	1932	1.01
Cca Industries Inc	Goods for Drug, food, and mass-merchandise retail chains	5.29M	1983	0.56

Notes: Avon Filed for bankruptcy in 2024. Beta measures the systematic risk of the stock of the company.

Due to differences in data availability across firms during the sample period, we constructed an unbalanced panel dataset comprising 1,362 observations, incorporating all available data for each firm.
The analysis incorporates both quarterly financial metrics and monthly macroeconomic indicators that potentially influence corporate Q ratios. The quarterly firm-specific variables include the current ratio, representing current assets divided by current liabilities, which indicates a company's capacity to fulfill short-term financial obligations within twelve months. Higher current ratios suggest improved liquidity positions, theoretically supporting positive relationships with firm valuation and Q ratios. The quick ratio, calculated as liquid assets divided by current liabilities, provides a more stringent liquidity measure by excluding inventory from current assets. This metric, also termed the acid test ratio, evaluates a firm's ability to satisfy immediate obligations using readily convertible assets including cash, cash equivalents, marketable securities, and net accounts receivable. Both liquidity ratios are anticipated to demonstrate positive associations with Q values given their indication of financial stability.

Operating income after debt serves as another quarterly variable, representing earnings available after debt service obligations. This measure logically correlates positively with firm valuation since higher post-debt income suggests stronger operational performance and cash generation capacity. The debt-to-asset ratio, computed as total debt divided by total assets, captures leverage levels and financial structure decisions. This ratio presents complex theoretical relationships with firm value, as moderate debt levels can enhance returns through leverage effects and tax benefits from interest deductibility, while excessive borrowing increases financial distress risk and constrains operational flexibility. The optimal debt level balances these competing forces, with our sample data suggesting a positive association between debt ratios and Q values within the examined range.

Monthly macroeconomic variables capture broader economic conditions and uncertainty levels affecting firm valuations. The economic policy uncertainty index, developed by Baker and colleagues in 2016, quantifies policy-related uncertainty through systematic analysis of major newspaper coverage. This index identifies articles containing terms related to uncertainty, economic conditions, and policy matters from ten prominent U.S. daily newspapers, creating a monthly measure of policy uncertainty since 1985. Articles qualify for inclusion when they contain at least one term from each of three categories: uncertainty terminology, economic references, and policy-related words including Congress, deficit, Federal Reserve, legislation, regulation, or White House.

Consumer sentiment data originates from the University of Michigan's monthly surveys conducted by the Institute for Social Research, involving approximately 500 telephone interviews with representative U.S. households. The survey instrument comprises five core questions examining current financial situations, future financial expectations, business condition forecasts for both one-year and five-year horizons, and purchasing timing assessments for major household items. These responses generate two component indices: current economic conditions based on present financial situations and purchasing timing, and consumer expectations derived from future-oriented questions. The overall consumer sentiment index combines these components using historical weighting and normalization procedures, with December 1966 serving as the baseline value of 100.

Inflation expectations emerge from the same University of Michigan survey process, where respondents provide open-ended responses regarding anticipated price changes over twelve-month and five-year periods. The survey methodology employs median values rather than arithmetic means to minimize outlier influence, generating robust measures of consumer inflation expectations. These expectations significantly influence economic behavior, as anticipated price increases can prompt immediate spending decisions or wage demands, creating feedback loops that affect actual inflation rates. Federal Reserve policymakers closely monitor these expectations for monetary policy guidance, particularly regarding interest rate adjustments.

Recession probability data comes from the Federal Reserve Bank of St. Louis database, representing smoothed U.S. recession probabilities derived through dynamic factor modeling techniques. This methodology aggregates information from multiple economic indicators including GDP growth, industrial production, employment statistics, and related variables to estimate latent factors capturing common economic movements. The model employs Markov switching frameworks allowing economic transitions between expansion and recession states with estimated probabilities based on historical patterns. The smoothing process incorporates past, present, and anticipated data to enhance probability estimate accuracy at each time point.

The recession probability model specifically utilizes four monthly coincident variables: non-farm payroll employment, industrial production indices, real personal income excluding transfer payments, and real manufacturing and trade sales. This approach, originally developed by Chauvet in 1998 and subsequently refined by Chauvet and Piger in 2008 and Chauvet and colleagues in 2024, provides comprehensive recession risk assessments for policymakers, economists, and market participants. The dynamic nature of these probabilities offers real-time economic condition evaluations, supporting both short-term forecasting and strategic planning initiatives across various economic sectors.

Table 2 presents comprehensive summary statistics for all variables employed in our analysis, providing descriptive insights into the distributional characteristics of both firm-specific financial metrics and macroeconomic uncertainty measures throughout the sample period.

Table 2: Unit root tests and descriptive statistics Q1/1985 to Q4/2022

Panel A: Levine, Lin and chu (LLC) Unit Root Test of Panel Financial Variables					
Null: Unit root (assumes common unit root process)					
	CR	DA	OIAD	Q	QR
LLC	-2.824 [a]	-0.444	-0.854	-1.867 [a]	-1.790 [a]
Panel B: Uncertainty Variables					
	EPU	Rec_Risk	INFEXP	Consconf	
ADF	-5.069 [a]	-4.401 [a]	-5.507 [a]	-3.700 [a]	
PP	-5.291 [a]	-4.453 [a]	-5.698 [a]	-3.483 [a]	
Hausman Test of Random VS. Fixed Effect Ho: Random Effect in cross sections Ha: Fixed effect in cross sections $\chi^2 = 8.269$ [a]					
Panel C: Descriptive statistics of the financial variables for the sample companies					
	CR	DA	OIAD	Q	QR
Mean	1.673	0.278	399.646	3.218	1.089
Median	1.452	0.261	59.504	2.241	0.940
Min	0.494	0.000	-5.562	0.057	0.275
Max	8.772	0.841	919.489	24.943	5.537

Notes: Notes: Levine, Lin and chu t*(LLC) unit root test assumes cross-sectional independence among variables of the panel data. The null hypotheses for ADF and PP tests is that a series is nonstationary. Intercepts were included in the ADF and PP tests. a, b represent significance at 1 and 5 percent levels. Random effect is rejected based on the Hausman test. OIAD is in millions of dollars.

4. Methodology

This study relies on two distinct empirical techniques: panel quantile regression and the panel vector autoregressive MIDAS model. While we offer a brief overview of each, the detailed technical exposition is not the central purpose of this paper. For readers interested in a more comprehensive understanding of these methodologies, we direct them to the foundational contributions of Koenker (2004), Canay (2011), Koenker and Ng (2005), Sheather (1988), and Koenker & d'Orey (1987), Koenker 2005), Koenker and Machado (1999), Lamarche (2010), Galvao (2011, 2019, 2020), and Canova and Ciccarelli (2013), Hendricks and Koenker (1992) among others. Our specific application of these methods is largely guided by the framework presented in Adrangi et al. (2023a, 2023b, 2024a, 2025a, b, 2026 (forthcoming)).

a. Panel quantile regression (PQR)

Panel quantile regression (PQR) is a sophisticated variant of standard quantile regression, specifically designed to estimate model coefficients that vary across the conditional distribution of the dependent variable, q. This method is particularly adept at accommodating both firm-specific and time-specific influences on the outcome. The development of PQR represents a significant advance, allowing researchers to estimate conditional quantile regression models that incorporate latent individual heterogeneity in panel datasets. Such datasets are characterized by observations on a dependent variable, $y_{it,}$ and a p-dimensional vector of regressors, xit, for a set of subjects i observed over multiple time periods t.

The core advantage of PQR over methods that merely estimate the conditional mean lies in its capacity to capture heterogeneity more effectively. While mean-based approaches provide an average effect, PQR reveals how explanatory variables influence different parts of the outcome distribution. This is crucial because relationships between variables are rarely uniform across an entire population. For example, the

impact of a certain policy on a firm's q might be vastly different for firms already at the top of the valuation scale compared to those at the bottom. This nuanced understanding is central to the PQR approach, which builds on the seminal work of Koenker and Bassett (1978) and Koenker & d'Orey (1987). Since its introduction, scholars like Portnoy (1991), Powell (1986), Koenker (2004), He and Zhu (2003), Angrist et al. (2006), and Golchin & Rekabdar (2024) have further generalized quantile regression, leading to its widespread deployment in finance and economics. The application of standard quantile regression to panel data, giving rise to PQR, represents a natural and powerful extension.
PQR estimates are also notably more robust to outliers than OLS, offering more reliable results in datasets where extreme values might unduly influence conventional analyses. This feature is particularly valuable given the diverse range of q values observed in our firm-level panel data, where a few exceptionally high or low values could easily skew mean-based results. By providing a broader picture across different parts of the distribution, PQR helps overcome this limitation. Closely following the approach of Adrangi et al. (2023a, 2023b, 2026 (forthcoming)), we employ PQR models due to their known nonlinearity (Galvao, 2011; Galvao et al., 2019, 2020) and their inherent robustness i the presence of extreme events and asymmetric dependence, situations where linear assumptions are often inadequate (Geraci, 2019; Yu et al., 2003). Their ability to allow coefficient estimates to vary across the dependent variable's distribution provides a more accurate representation of the complex relationships at play.

Given a random variable Y (q) with probability distribution function

$$F(y) = \text{Prob}(Y \leq y)$$

so that for $0 < \tau < 1$ the τth quantile of Y is defined as the minimum y satisfying

$$F(y) \geq \tau:$$

$$Q(\tau) = \inf\{y : F(y) \geq \tau\}.$$

Then the empirical distribution function is

$$F_n(y) = \sum_s l(Y_i \leq y),$$

in which $l(.)$ is a binary function that takes the value 1 if $Y_i \leq y$ is true and 0 otherwise. The resulting empirical quantile may be expressed as an optimization problem as

$$Q_n(\tau) = \arg\min\left\{\sum_i \rho_\tau(Y_i - \omega)\right\},$$

in which $\rho_\tau(w) = w(\tau - 1(w < 0))$ asymmetrically assigns weights to positive and negative values in the estimation process.

We assume a linear specification for the conditional quantile of the dependent variable Q given values for the vector of explanatory variables X such that

$$Q(\tau \mid X_i, \beta(\tau)) = X_i^{'}\beta(\tau). \quad (1)$$

In equation (1), $\beta(\tau)$ is the vector of coefficients associated with the τ th quantile.

Then, the conditional quantile regression estimator is as shown by Adrangi et al. (2023a)

$$\beta_n(\tau) = \arg\min_{\beta(\tau)} \left\{ \sum_i \rho_\tau (Y_i - X_i^{'}\beta(\tau)) \right\}.$$

The quantile regression estimator is derived as the solution to a linear programming problem. We apply an adapted form of Koenker and D'Orey's (1987) iteration of the Barrodale and Roberts' (1973) simplex algorithm.

Recent years have seen a significant push towards integrating more adaptive representations of unobserved heterogeneity within panel data models. This trend is a direct result of substantial methodological advancements in linear panel data analysis, which have improved the estimation of complex models featuring interactive effects and factor structures (Pesaran, 2006; Bai, 2009; Moon and Weidner, 2015, 2017). For panel datasets characterized by a large number of time periods (T), panel quantile estimation is specifically conducted using a particular optimization routine.

$$\arg\min_{\theta, f, \beta \in G \times F \times B} E(\lambda_\tau (y - \mathbf{x}^{'}\boldsymbol{\beta} - \varphi^{'}\mathbf{f})),$$

Where φ is a r-dimensional vector of individual factor loadings, r is the number of latent factors and $\boldsymbol{f}$ is a vector of unobserved time-varying factors,. In this formulation the individual effects enter the model such that $\varphi^{'}\mathbf{f} = \varphi_1 + \sum_r \varphi_k f_k$ if f_1 is normalized to one.

In this paper we opt for this approach to incorporating subject-specific heterogeneity φ and avoid the problem of additive separable unobserved heterogeneity assuming that $\boldsymbol{f}$ affects the dependent variable.

Consider the panel quantile regression with fixed effects given by equation (2).

$$Qy_{it}(\tau \mid X_{it}, \varphi_i) = x_{it}^{'}\beta(\tau) + \varphi(\tau)_i, \text{ where } i = 1, \ldots, n; t = 1, \ldots, T. \tag{2}$$

Estimating the quantile regression in (2) presents a problem of incidental paramters as there are incidental parameters that cannot be eliminated.

Kato et al. (2012) studied the properties of quantile regression in a model where the fixed effects are captured by dummy variables. The estimator is consistent and asymptotically normal when both n → ∞ and T →∞ with $n^2[\ln(n)]^3/T \to 0$. However, this approach leads to explosive conditions as in practice n> T. For instance if T = 30, n = 200, then $n^2[\ln(n)]^3 = 133{,}862$. An alternative is to deploy the method of moments estimator to equation (2).

y_{it} may be written as

$$y_{it} = \alpha_i + x_{it}^{'}\beta + (\gamma_i + x_{it}^{'}\delta)u_{it},$$

where

$$\varphi(\tau)_i = \alpha + \gamma_i Q_u(\tau)$$

and

$$\beta(\tau) = \beta + \delta Q_u(\tau).$$

Assuming that u_{it} and x_{it} are independent and that

$$\Pr ob((\gamma_i + x'_{it}\delta) > 0) = 1,$$

we can estimate the model parameters using two fixed effects regressions and deriving a univariate quantile. We deploy this methodology to estimate the parameters of equation (4). To confirm and examine the robustness of our findings, we also estimate panel VAR-MIDAS models. The objective of this exercise is to derive impulse responses of the Q to various shocks to the model variables.

b. Panel VAR- MIDAS

The second tool of our methodology is the panel vector autoregressive MIDAS model (PVM). This methodology is explained at length in Adrangi (2025a, b and forthcoming 2026). We follow their explanation closely as the methodology does not constitute the core of this paper and is presented here for the benefit of readers. For this study, we utilize PVM model, a form of the well-known Vector Autoregressive (VAR) framework. PVM models are especially effective for panel datasets that combine observations from different time intervals, such as quarterly and monthly frequencies. This is a significant advantage for our research, as our data includes both, and PVM allows for direct analysis without needing to convert all observations to the same frequency. These models are highly adept at capturing the complex, interdependent relationships among variables, similar to traditional VARs. Since VAR methodologies are thoroughly documented in existing research, we will only summarize their core principles. The specific reduced-form PVM we are using avoids the need to pre-assign variables as exogenous or endogenous, instead treating all variables within the model as inherently intertwined. This flexible approach is preferable because, in reality, the distinctions between exogenous and endogenous roles in economic and financial systems are often ambiguous.

A VAR model of order p may be expresses as equation (3)

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + \varepsilon_t \ , \tag{3}$$

where,

$y_t = (y_{1t} y_{2t} .....y_{jt})'$ is a vector of Jx1 model endogenous variables,

$A_1 A_2 .....A_p$ is the matrix of model coefficients that will be estimated.

$\varepsilon_t = (\varepsilon_{1t}\varepsilon_{2t}....\varepsilon_{jt})$ is a j by1 vector of white noise model innovations with the following matrix of variances and characteristics.

$$E(\varepsilon_t) = 0, E\ (\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon$$

$$E(\varepsilon_t \varepsilon'_s) = 0 \text{ for } t \neq s.$$

The fundamental concept behind PVM models involves leveraging past values of high-frequency data to forecast or explain the present or future states of low-frequency data. This is achieved by estimating the dynamic relationships between these variables, effectively blending both high- and low-frequency observations.

To illustrate, consider a simple PVM with *m* high-frequency periods for each low-frequency observation. For example, if we have monthly data for one variable, we might use twenty daily observations from other variables to explain it. Applying this to panel data introduces an additional layer of complexity. However, the distinction between a PVM and a VAR-MIDAS model primarily lies in the low-frequency data, which, in a PVM context, forms an unbalanced panel.

To demonstrate a PVM model, let us assume that a VAR consists of n_{Lt} variables observed at low frequency and $n_{Ht,}$ at high frequency. Forming a VAR from the high and low frequency variables in a VAR produces the system of equation (2)

$$\begin{bmatrix} Y_{H.t_t,1} \\ Y_{H.t_t,2} \\ \cdots\cdots \\ Y_{H.t_t,n} \\ Y_H, t_L \end{bmatrix} = \begin{bmatrix} \Gamma_j^{1,1} & \Gamma_j^{1,2} & \dots & \Gamma_j^{1,n} & \Gamma_j^{1,n+1} \\ \Gamma_j^{2,1} & \dots & \dots & \dots & \Gamma_j^{2,n+1} \\ \dots & & & & \dots \\ \Gamma_j^{n,1} & \dots & \dots & \Gamma_j^{n,n} & \Gamma_j^{n,n+1} \\ \Gamma_j^{n+1,1} & \dots & \dots & \Gamma_j^{n+1,n} & \Gamma_j^{n+1,n+1} \end{bmatrix} \begin{bmatrix} Y_{H.t_t-j,1} \\ Y_{H.t_t-j,2} \\ \dots \\ Y_{H.t_t-j,n} \\ Y_{L.t_t-j} \end{bmatrix} + \begin{bmatrix} \mathrm{E}_{H.t_L,1} \\ \mathrm{E}_{H.t_L,2} \\ \dots \\ \mathrm{E}_{H.t_L,n} \\ \mathrm{E}_H, t_L \end{bmatrix}, \tag{4}$$

where matrix $\Gamma_j^{a,b}$ is K_H*K_H, $\Gamma_j^{n+1,b}$ K_L*K_H, $\Gamma_j^{a,n+1}$ K_H*K_L for all j, a,b= 1,2,.. n, and $\Gamma_j^{n+1,n+1}$ is K_L*K_L.

In this model, Y_{Ht} and Y_{Lt} represent the high and low-frequency variables observed at time t. The lagged values of Y, denoted as Y(t-j), capture the autoregressive component of the low-frequency variable. The coefficient matrices $\Gamma_j^{\alpha,\beta}$ represent the parameters to be estimated, and E_{H,t_L} and E_{L,t_L} are the high and low frequency white noise error term vectors.

Ghysels et al. (2004 and 2016) offers the Bayesian PVM estimation. This methodology requires specifying prior distributions for the model coefficients and the covariance matrix of the white noise residuals. Combining the specified priors with VAR likelihood generates the conditional posteriors of the model coefficients as well as the innovations covariance matrix as

$(\beta|y,\Sigma) \sim N(\bar{\beta},\bar{\Omega})$ and $(\Sigma|y,\beta) \sim IW(\bar{Q},\bar{\varpi})$,

where,

$$\bar{\Omega} = (\underline{\Omega}^{-1} + (\hat{\Sigma}^{-1} \otimes (X''X')^{-1}))^{-1}$$
$$\bar{\beta} = \bar{\Omega}(\underline{\Omega}^{-1}\underline{\beta} + (\hat{\Sigma}^{-1} \otimes (X'')y)$$
$$\bar{Q} = \underline{Q} + \mathrm{E}'\mathrm{E}$$
$$\varpi = \underline{\varpi} + \mathrm{T}$$

Our model's parameters draw their prior distribution from Litterman's (1986) framework, wherein prior means are established at zero, with the sole exception of the first lag terms. Ghysels et al. (2016) subsequently introduce modifications to Litterman's initial assumptions; specifically, they assign a distinct hyper-parameter to each own-lag term based on its observation frequency. Additionally, the high-frequency series are modeled as an AR(1) process, which manifests as exponential parameters within the low-frequency context. The prior variance for the model coefficients is also adjusted to incorporate variances across different frequencies.

PVM models offer several distinct benefits for econometric analysis. They allow researchers to integrate high-frequency data, which captures rich, short-term dynamics, directly into the study of low-frequency variables. This integration is crucial for illuminating the complex relationships and transmission mechanisms that exist between economic indicators operating on different time scales. Ultimately, PVM models represent a powerful asset in econometric modeling, particularly for datasets composed of mixed-frequency observations. They enable the coherent integration of diverse temporal data, providing deep insights into dynamic interconnections. By simultaneously accounting for both short-term variability and

long-term patterns, PVM models, like the VAR-MIDAS variants, significantly advance our understanding of complex economic systems.
To ensure that the model variables are stationary, we deploy two standard tests, the Augmented Dickey-Fuller and Phillips-Perron and report their results in Table 2.
In the following, we discuss the empirical findings of this paper and propose managerial strategies that may effectively safeguard firm value in both the short and long term.

5. Empirical Findings and their Managerial Implications

To prepare our data for panel quantile regression (PQR) and PVM, we perform the Hausman test for fixed vs. random effects, and stationarity tests on the variables in our panel sample. Table 2 displays the outcomes of the Levin, Lin, and Chu t* (LLC) test of stationarity for panel data, which indicates that DA and OIAD are non-stationary. Therefore, these variables underwent first differencing to ensure their stationarity before being included in the PVM model. and subsequent statistical models. Meanwhile, T separately confirmed that the monthly uncertainty series are indeed stationary. Table 2 also shows the random effect in cross sections is rejected in favor of fixed effect.

a. Findings of the Panel Quantile Regressions
The quantile regression to be estimated is equation (5)

$$Q= f(cr, da, oiad, qr, epu, rec\_risk, infexp, consconf). \quad (5)$$

Table 3 shows that economic and economic policy indicators show varying association with the Firms' Tobin's Q in the consumer non-durable sector in the US.

Table 3: Panel Quantile Regression Estimation Results

Quantile	10	25	50	75	90
CR	-0.899	2.076[a]	1.748 [a]	1.457 [a]	1.209 [a]
	(0.800)	(0.282)		(0.334)	(0.250)
Dda	0.379	0.440	-0.226	0.702	-6.225[a]
	(1.048)	(0.967)	(1.464)	(1.031)	(2.203)
Doiad	9.2*e-05	8.1*e-06	0.0001	0.036 [a]	0.004 [a]
	(0.0002)	(0.0001)	(0.0003)	(0.0002)	(0.002)
QR	1.984[a]	2.169[a]	1.514[a]	0.758[b]	-0.087
	(0.403)	(0.320)	(0.415)	(0.383)	(0.451)
EPU	0.0011 [a]	0.0010 [a]	0.002 [a]	0.001 [a]	0.003 [a]
	(0.0002)	(0.0002)	(0.0003)	(0.0006)	(0.0008)
Cconf	0.0107 [a]	0.0186 [a]	0.027 [a]	0.048 [a]	0.095[a]
	(0.0030)	(0.0022)	(0.0027)	(0.004)	(0.009)
Infexp	0.3042 [a]	0.227 [a]	0.278 [a]	0.302 [b]	0.018
	(0.0490	(0.055)	(0.089)	(0.107)	(0.165)
Rec_risk	.0.0007	-0.0002	-0.0004	0.0003	0.001
	(0.0007)	(0.0005)	(0.0009)	(0.001)	(0.002)
Ps_Rsq	0.087	0.093	0.083	0.083	0.102
Obj. ft.	294.62	630.37	1017.10	1091.20	720.593

Notes: Huber Sandwich Standard Errors & Covariance.Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall-Sheather, bw=0.091941. a,b statistically significant at 0.01 and 5% percent levels or less.

The finding that economic policy uncertainty, consumer confidence, and inflationary expectations all exert a positive impact on the value of U.S. firms in the consumer nondurable sector—across all quantiles of Tobin's Q—may appear counterintuitive at first glance. However, a closer inspection of the nature of the sector, investor behavior, and the macroeconomic environment provides a consistent narrative that supports such a relationship.

Consumer nondurable goods, which include essential items such as food, beverages, toiletries, and household products, tend to exhibit stable demand regardless of broader economic fluctuations. During periods of heightened economic policy uncertainty, investors often seek refuge in industries that are less susceptible to the volatility affecting discretionary spending or capital-intensive sectors. Because consumer nondurable goods represent necessities, firms in this sector tend to generate consistent revenues and cash flows even in turbulent environments. This defensive characteristic increases their relative attractiveness to investors during times of uncertainty, contributing to an upward valuation adjustment across all segments of firm value as measured by Tobin's Q.

Consumer confidence, while typically a leading indicator for overall economic activity, plays a particularly nuanced role in the nondurable sector. When consumer sentiment is strong, households are more likely to maintain or increase consumption levels, including nondurable goods. More importantly, confidence amplifies purchasing behavior not just in quantity but also in brand preference and loyalty—traits that benefit established firms with strong market positions. Since many consumer nondurable companies rely on brand equity and operational efficiency, they are well positioned to capture value from increased consumption intensity during optimistic periods. Even in lower quantiles of firm value, strong consumer confidence can lift expected earnings and margins, thereby improving investors' valuation assessments consistently across the distribution.

Inflationary expectations, though often associated with margin pressures, can have a favorable effect on firms in the consumer nondurable sector for several reasons. First, many of these firms possess significant pricing power due to brand loyalty and the habitual nature of their products. This allows them to pass cost increases onto consumers without a significant loss in volume, preserving or even enhancing profitability. Second, when inflation is anticipated rather than abrupt, firms can proactively manage inventories, input contracts, and supply chain logistics to capitalize on rising prices. These strategic responses can enhance the forward-looking earnings profile and market value of such firms. Investors, recognizing this resilience and adaptability, may reward these firms with higher valuations across all performance tiers. Lastly, inflationary expectations often prompt consumers to stock up on essential nondurable goods in anticipation of rising prices. This forward-buying behavior boosts sales and revenues for firms in the sector, thereby contributing to an increase in their Tobin's Q.

The positive relationship observed across all quantiles of Tobin's Q implies that the market does not restrict its optimism to only the most efficient or successful firms in the sector. Even firms in the lower end of the value distribution benefit from the sector-wide reallocation of investor capital during periods marked by uncertainty or inflationary expectations. This broad-based valuation support underscores the structural strengths of the consumer nondurable industry: its predictable demand, scalable cost structures, and ability to maintain pricing integrity. These attributes allow firms to protect and even grow their intrinsic value despite the macroeconomic headwinds that typically erode firm valuations in more cyclical or capital-intensive sectors.

In sum, the consistent positive influence of economic policy uncertainty, consumer confidence, and inflationary expectations on Tobin's Q across the entire value distribution of consumer nondurable firms reflects the market's recognition of the sector's defensive nature and strategic agility. Investors appear to systematically reallocate capital toward this sector in both favorable and adverse economic climates, reinforcing firm value regardless of its starting point. This pattern not only validates the empirical findings but also aligns with theoretical expectations about investor behavior, sectoral characteristics, and the interpretation of macroeconomic signals.

Recessionary risk, while typically associated with declines in firm valuations across most sectors, does not exert the same downward pressure on Tobin’s Q for firms in the consumer nondurables sector. This resilience stems from the essential nature of the goods these firms provide—items such as food, beverages, hygiene products, and household necessities that remain in demand regardless of broader economic conditions. During recessions, consumers may reduce spending on discretionary or luxury goods, but they continue to purchase nondurables out of necessity, often shifting their consumption patterns rather than cutting them entirely.

This stability in demand helps preserve revenue streams and operating margins for firms in the sector, which in turn supports their asset utilization and expected future profitability—two key drivers of Tobin’s Q. Moreover, investors seeking stability during downturns often rotate capital into defensive sectors like consumer nondurables, recognizing their capacity to weather economic contractions. This countercyclical inflow of investor capital can help maintain, or even elevate, market valuations relative to the replacement cost of assets. Consequently, even in the face of recessionary risk, Tobin’s Q for consumer nondurable firms tends to remain stable across the value distribution, reflecting the sector's fundamental insulation from cyclical downturns and its perceived role as a safe harbor in uncertain economic times.

Turning to financial variables that influence the Tobin’s Q of firms in the consumer nondurable goods sector, the observed positive associations with the current ratio, quick ratio and operating income after depreciation reflect the market’s valuation of liquidity, operational efficiency, and financial health in this essential and often low-margin industry.

The current ratio and quick ratio—both measures of liquidity—signal a firm’s ability to meet short-term obligations with readily available assets. Both CR and QR show positive association with Q in Table 3 in almost every quantile of Q. In the context of consumer nondurables, where inventory turnover is typically high and operations depend on efficient working capital management, strong liquidity provides a cushion against supply chain disruptions, input cost volatility, or temporary shifts in demand. A high current or quick ratio reassures investors that the firm is unlikely to face cash flow problems that could hinder operations, especially during uncertain economic conditions. This operational flexibility and financial resilience enhance investor confidence and support a higher Tobin’s Q, as the firm is seen as better equipped to sustain profitability and protect asset values.

Operating income after depreciation, a measure of a firm’s core earnings capacity net of the wear and tear on its capital base, reflects the underlying efficiency and productivity of the business. In the nondurable sector—characterized by scale economies, tight margins, and brand competition—firms that consistently generate strong operating income signal superior cost control, effective pricing, and competitive positioning. These factors directly influence expectations of future cash flows, which are integral to the market’s assessment of firm value relative to asset replacement cost. As a result, firms with higher operating income after depreciation tend to enjoy higher Tobin’s Q values, as investors reward sustained operational performance and efficient asset utilization. Table 3 shows that the OIAD is positively associated with Q in this industry in the higher quantiles of Q.

In contrast, the debt-to-asset ratio—an indicator of financial leverage—may exhibit a negative relationship with Tobin’s Q in this sector. While some degree of leverage can enhance returns, excessive debt is often viewed unfavorably, particularly for firms operating in industries with relatively stable but modest profit margins. High leverage increases financial risk, reduces flexibility in managing operating costs or investing in innovation and branding, and may impose burdensome interest obligations. In the nondurable consumer goods sector, which depends heavily on consistent brand investment and supply chain reliability, high debt levels can constrain strategic choices and increase vulnerability to even minor revenue shocks. Consequently, the market may discount the value of highly leveraged firms, resulting in a lower Tobin's Q. This reflects concerns that future returns may be insufficient to justify current valuations once liabilities and risk exposure are fully considered.

Table 4 reports the findings of the Granger causality test between the macroeconomic variables, the focus of this paper, and Q for the firms in this industry. These findings bolster the results reported in Table 3.

Table 4: Wald test of Granger Causality based on the Panel Quantile Regression

Null Hypothesis	Chi-sq
consconf Does not Granger Cause q	13.374 [a]
EPU Does not Granger Cause q	11.793 [a]
infexp Does not Granger Cause q	9.043 [c]
Rec_risk Does not Granger Cause q	6.466

Notes: [a, b] represent significance at 1 and 5 percent levels. Significance of the Wald statistic leads to the rejection of the null hypothesis.

The finding that economic policy uncertainty, consumer confidence, and inflationary expectations Granger cause Tobin's Q in the consumer nondurable sector suggests that changes in these macroeconomic variables provide predictive information about future firm value in this industry. Economic policy uncertainty likely influences investor sentiment and capital allocation, prompting a shift toward stable, defensive sectors like nondurables, thereby affecting valuations. Similarly, rising consumer confidence signals stronger expected demand, while inflationary expectations may lead to increased purchasing and allow firms with pricing power to maintain margins—both of which support higher Q values. In contrast, recessionary risk does not Granger cause Tobin's Q in this sector, consistent with the essential nature of nondurable goods. Demand for these products remains relatively stable even in downturns, insulating firm value from recession-driven fluctuations and reducing the predictive power of recession indicators for Q in this industry.

The impulse response analysis presented in Figure 1 reveals that positive shocks to consumer confidence, economic policy uncertainty (EPU), and inflationary expectations (infexp) lead to significant increases in Tobin's Q for firms in the nondurable consumer goods sector for several quarters. These results suggest that investors view this sector as resilient and responsive to shifts in macroeconomic sentiment and expectations. When consumer confidence rises, firms in this sector benefit from increased or sustained demand, as households are more willing to spend on everyday essentials. Similarly, in times of elevated policy uncertainty, investors tend to reallocate capital toward defensive sectors like nondurable consumer goods, which are perceived as safer and more stable. Inflationary expectations also contribute positively, as consumers often accelerate purchases of essential goods in anticipation of rising prices, boosting short-term sales and revenues. Moreover, firms in this sector frequently possess the pricing power needed to preserve margins under inflationary pressure.

In contrast, shocks to recessionary risk do not significantly or positively affect Tobin's Q in this industry. This aligns with the sector's core characteristic: demand for nondurable essentials remains relatively inelastic even during economic downturns. As a result, the valuation of firms in this sector is less sensitive to cyclical recession indicators. These findings support the estimated results reported in Table 3 of this paper, reinforcing the notion that Tobin's Q in the consumer nondurable sector is more responsive to shifts in sentiment and expectations than to conventional business cycle risks.

6. Summary, Conclusions, and Managerial Implications

This paper investigates the relationship between macroeconomic and policy-related uncertainties and firm value, as measured by Tobin's Q, for a sample of U.S. firms in the consumer nondurable goods sector. Using panel quantile regression and panel MIDAS-VAR models, the analysis focuses on how different forms of uncertainty influence firm valuation across the distribution of Tobin's Q. The dataset comprises nine major U.S. firms and spans the period from 1980 through the first quarter of 2022. In addition to macroeconomic variables, the models incorporate key firm-specific financial indicators, including the current ratio, quick ratio, debt-to-asset ratio, and operating income after depreciation.

The empirical findings indicate a consistent positive association between Tobin's Q and three macroeconomic variables: economic policy uncertainty, consumer confidence, and inflationary expectations. These variables not only exhibit significant contemporaneous associations with firm value but are also shown to Granger cause Tobin's Q, highlighting their predictive power over valuation dynamics in this sector. In contrast, recessionary expectations do not appear to have a significant or positive effect on Tobin's Q. This result aligns with the essential nature of the products in the consumer nondurable sector, where demand remains relatively stable during economic downturns, insulating firm value from the effects of recession-related risk.

These findings carry important implications for managers and decision-makers in the consumer nondurable industry. First, firms should closely monitor shifts in consumer sentiment and inflation expectations, as these indicators may offer early signals of changes in firm valuation. Second, given the sensitivity of Tobin's Q to policy uncertainty, firms that maintain operational flexibility and strong liquidity positions may be better positioned to attract investor capital during periods of broader economic ambiguity. Finally, while recessionary risk does not directly depress valuations in this sector, maintaining brand strength and supply chain resilience can further reinforce the sector's defensive appeal. Understanding these dynamics can help managers navigate uncertain environments while preserving or enhancing firm value.

The findings of this study also offer several implications for investors and money managers. First, the positive association between Tobin's Q and variables such as economic policy uncertainty, consumer confidence, and inflationary expectations suggests that firms in the consumer nondurable sector can serve as a stable component of investment portfolios during periods of macroeconomic uncertainty. This sector appears to attract capital when broader economic signals are mixed, reinforcing its role as a defensive investment option.

Second, the evidence that these macroeconomic variables Granger cause firm value highlights the importance of monitoring forward-looking indicators when making sector allocation decisions. Investors who track shifts in consumer sentiment and policy-related uncertainty may be better positioned to anticipate valuation changes and adjust exposure accordingly.

Third, the sector's apparent insulation from recessionary risk supports the case for including consumer nondurable firms as a hedge against economic downturns. Since these firms provide essential goods with relatively inelastic demand, their valuations are less vulnerable to cyclical pressures, offering stability when other sectors may experience sharp declines.

Lastly, firm-level indicators such as strong liquidity and efficient operations appear to enhance responsiveness to favorable macroeconomic signals. Money managers may therefore prioritize firms within this sector that demonstrate solid balance sheets and consistent operating income, as these characteristics align with the factors shown to support higher valuations over time.

Declarations

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References

Adrangi, B., & Raffiee, K. (1999). On total price uncertainty and the behavior of a competitive firm. The American Economist, 43(2), 59-65.

Adrangi, B., Chatrath, A., Kolay, M., & Raffiee, K (2024a) Enterprise Value, Economic and Policy Uncertainties: The Case of US Air Carriers. Journal of Theoretical Accounting Research, 20(1), 123-175.

Adrangi, B., Chatrath, A., & Raffiee, K. (2023a). S&P 500 volatility, volatility regimes, and economic uncertainty. Bulletin of Economic Research, 75(4), 1362-1387.

Adrangi, B., Chatrath, A., Maitra, D., & Sengupta, A. (2024b). Is the Influence of Oil Shocks on Economic Policy Uncertainty Fading? American Business Review, 27(2), 5.

Adrangi, B., Chatrath, A., & Raffiee, K. (2024c). U.S. Diesel Fuel Price Volatility and Economic Policy Uncertainty. Oil, Gas & Energy Quarterly, 72 (3), 533-566.

Adrangi, B., Chatrath, A., & Raffiee, K. (2025b). Latin American Equities, Volatility Regimes, and the US Economic Policy Uncertainty. Bulletin of Applied Economics, Forthcoming.

Adrangi, B., Chatrath, A., Hatamerad, S. ,& Raffiee, K. (2025a). Equity Markets Volatility, Regime Dependence and Economic Uncertainty: The Case of Pacific Basin. Bulletin of Applied Economics, Bulletin of Applied Economics, 2025, 12(1), 75-105. https://doi.org/10.47260/bae/1215

Adrangi, B., Hatamerad, S., Kolay, M., & Raffiee, K . (2026). Economic and Policy Uncertainties and Firm Value: The Case of Consumer Durable Goods. Journal of Theoretical Accounting Research, Forthcoming. 22(2), 111-158.

Adrangi, B., & Hamilton, E. (2023b). Market concentration and performance: The case of the US airline industry. The Journal of Theoretical Accounting Research, 18(3), 54-78.

Angrist, J., Chernozhukov, V., & Fernández-Val, I. (2006). Quantile regression under misspecification, with an application to the US wage structure. Econometrica, 74(2), 539-563.

Bai, J. (2009). Panel data models with interactive fixed effects. Econometrica, 77(4), 1229-1279. Baker, S. R., Bloom, N., & Davis, S. J. (2016). Vol. 131 November 2016 Issue 4. The Quarterly Journal of Economics, 1593, 1636.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4), 1593-1636.

Baker, Scott, Bloom, Nicholas and Davis, Steven J. (2012), "Measuring Economic Policy Uncertainty," University of Chicago and Stanford University. Available at www.policyuncertainty.com

Baker, S. R., Bloom, N., & Davis, S. J. (2014). Measuring economic policy uncertainty. The Quarterly Journal of Economics, 129(4), 1631-1686.

Barrodale, I., & Roberts, F. D. (1973). An improved algorithm for discrete l_1 linear approximation. SIAM Journal on Numerical Analysis, 10(5), 839-848.

Butt, M. N., Baig, A. S., & Seyyed, F. J. (2023). Tobin's Q approximation as a metric of firm performance: an empirical evaluation. Journal of Strategic Marketing, 31(3), 532-548.

Canay, I. A. (2011). A simple approach to quantile regression for panel data. The econometrics journal, 14(3), 368-386.

Canova, F., & Ciccarelli, M. (2013). Panel Vector Autoregressive Models: A Survey☆ The views expressed in this article are those of the authors and do not necessarily reflect those of the ECB or the Eurosystem. In VAR models in macroeconomics–new developments and applications: Essays in honor of Christopher A. Sims (pp. 205-246). Emerald Group Publishing Limited.

Chauvet, M. (1998). An Economic Characterization of Business Cycle Dynamics with Factor Structure and Regime Switching. International Economic Review, 39, 969-996.

Chauvet, M. and J. Piger. (2008). A Comparison of the Real-Time Performance of Business Cycle Dating Methods. Journal of Business and Economic Statistics, 26, 42-49.

Chauvet, Marcelle and Piger, Jeremy Max, Smoothed U.S. Recession Probabilities [RECPROUSM156N], retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/RECPROUSM156N, July 1, 2024.

Danielsen, T. M. (2017). Effect of Exposure to Renewable Energy on Valuation of Oil and Gas Companies (Master's thesis, University of Stavanger, Norway).

Davis, S. J., Bloom, N., & Baker, S. R. (2013). Measuring economic policy uncertainty. NBER Working Paper, 21633.

Demir, E., & Ersan, O. (2017). Economic policy uncertainty and cash holdings: Evidence from BRIC countries. Emerging Markets Review, 33, 189-200.

Fadul, L. (2005). Ethical Behavior and CSR in the Oil and Gas Sector: Implications for Firm Value. Journal of Business Ethics, 145-161.

Flacco, P. R., & Kroetch, B. G. (1986). Adjustment to Production Uncertainty and the Theory of the Firm. Economic Inquiry, 24(3), 485-495.

Fooladi, I. (1986). The effect of proportional profit tax on the level of output, under uncertainty. Atlantic Economic Journal, 14(4), 90-94.

Fooladi, I., & Kayhani, N. (1991). Random Cost Functions and Production Decisions. Eastern Economic Journal, 17(2), 199-202.

Galbraith, John Kenneth. The Age of Uncertainty. Ed. Boston: Houghton Mifflin Company, 1977.

Galvao Jr, A. F. (2011). Quantile regression for dynamic panel data with fixed effects. Journal of Econometrics, 164(1), 142-157.

Galvao, A. F., & Poirier, A. (2019). Quantile regression random effects. Annals of Economics and Statistics, (134), 109-148.

Galvao, A. F., Gu, J., & Volgushev, S. (2020). On the unbiased asymptotic normality of quantile regression with fixed effects. Journal of Econometrics, 218(1), 178-215.

Geraci, M. (2019). Additive quantile regression for clustered data with an application to children's physical activity. Journal of the Royal Statistical Society Series C: Applied Statistics, 68(4), 1071-1089.

García-Gómez, C. D., Demir, E., Chen, M. H., & Díez-Esteban, J. M. (2022). Understanding the effects of economic policy uncertainty on US tourism firms' performance. Tourism Economics, 28(5), 1174-1192.

Golchin, B., and B. Rekabdar. (2024). Anomaly Detection in Time Series Data Using Reinforcement Learning, Variational Autoencoder, and Active Learning. Conference on AI, Science, Engineering, and Technology (AIxSET), Laguna Hills, CA, USA. 1-8, doi: 10.1109/AIxSET62544.2024.00007. https://ieeexplore.ieee.org/abstract/document/10770963

Golchin, B. and N. Riahi. (2021). Emotion detection in twitter messages using combination of long-short-term memory and convolutional deep neural networks. International Conference on Computer and Knowledge Engineering (ICCKE), World Academy of Science, Engineering and Technology International Journal of Computer and Information Engineering Vol:15, No:9.

Ghysels, E. (2004). The MIDAS touch: Mixed data sampling regression models. University of North Carolina.

Ghysels, E. (2016). Macroeconomics and the reality of mixed frequency data. Journal of Econometrics, 193(2), 294-314.

Hall, P., & Sheather, S. J. (1988). On the distribution of a studentized quantile. Journal of the Royal Statistical Society: Series B (Methodological), 50(3), 381-391.

He, X., & Zhu, L. X. (2003). A lack-of-fit test for quantile regression. Journal of the American Statistical Association, 98(464), 1013-1022.

Hendricks, W., & Koenker, R. (1992). Hierarchical spline models for conditional quantiles and the demand for electricity. Journal of the American statistical Association, 87(417), 58-68.

Jin, Y., & Jorion, P. (2006). Firm value and hedging: Evidence from US oil and gas producers. The journal of Finance, 61(2), 893-919.

Kato, K., Galvao Jr, A. F., & Montes-Rojas, G. V. (2012). Asymptotics for panel quantile regression models with individual effects. Journal of Econometrics, 170(1), 76-91.

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. Econometrica: journal of the Econometric Society, 33-50.

Koenker, R. W., & d'Orey, V. (1987). Algorithm AS 229: Computing regression quantiles. Applied statistics, 383-393.

Koenker, R., & Machado, J. A. (1999). Goodness of fit and related inference processes for quantile regression. Journal of the american statistical association, 94(448), 1296-1310.

Koenker, R. (2004). Quantile regression for longitudinal data. Journal of multivariate analysis, 91(1), 74-89.

Koenker, R. (2005). Quantile regression [M]. Econometric Society Monographs, Cambridge University Press, Cambridge.

Koenker, R., & Ng, P. (2005). Inequality constrained quantile regression. Sankhyā: The Indian Journal of Statistics, 418-440.

Lamarche, C. (2010). Robust penalized quantile regression estimation for panel data. Journal of Econometrics, 157(2), 396-408.

Litterman, R. B. (1986). Forecasting with Bayesian vector autoregressions: Five years of experience. In V. (. Zarnowitz, Business Cycles, Indicators, and Forecasting (pp. 87–156). Chicago: University of Chicago Press.

Moon, H. R., & Weidner, M. (2015). Linear regression for panel with unknown number of factors as interactive fixed effects. Econometrica, 83(4), 1543-1579.

Moon, H. R., & Weidner, M. (2017). Dynamic linear panel regression models with interactive fixed effects. Econometric Theory, 33(1), 158-195.

Pesaran, M. H. (2006). Estimation and Inference in Large Heterogeneous Panels with Multifactor Error Structure. Econometrica, 967–1012.

Phan, D., Nguyen, H., & Faff, R. (2014). Uncovering the asymmetric linkage between financial derivatives and firm value—The case of oil and gas exploration and production companies. Energy economics, 45, 340-352.

Portnoy, S. (1991). Asymptotic behavior of regression quantiles in non-stationary, dependent cases. Journal of Multivariate analysis, 38(1), 100-113.

Powell, J. L. (1986). Censored regression quantiles. Journal of econometrics, 32(1), 143-155.

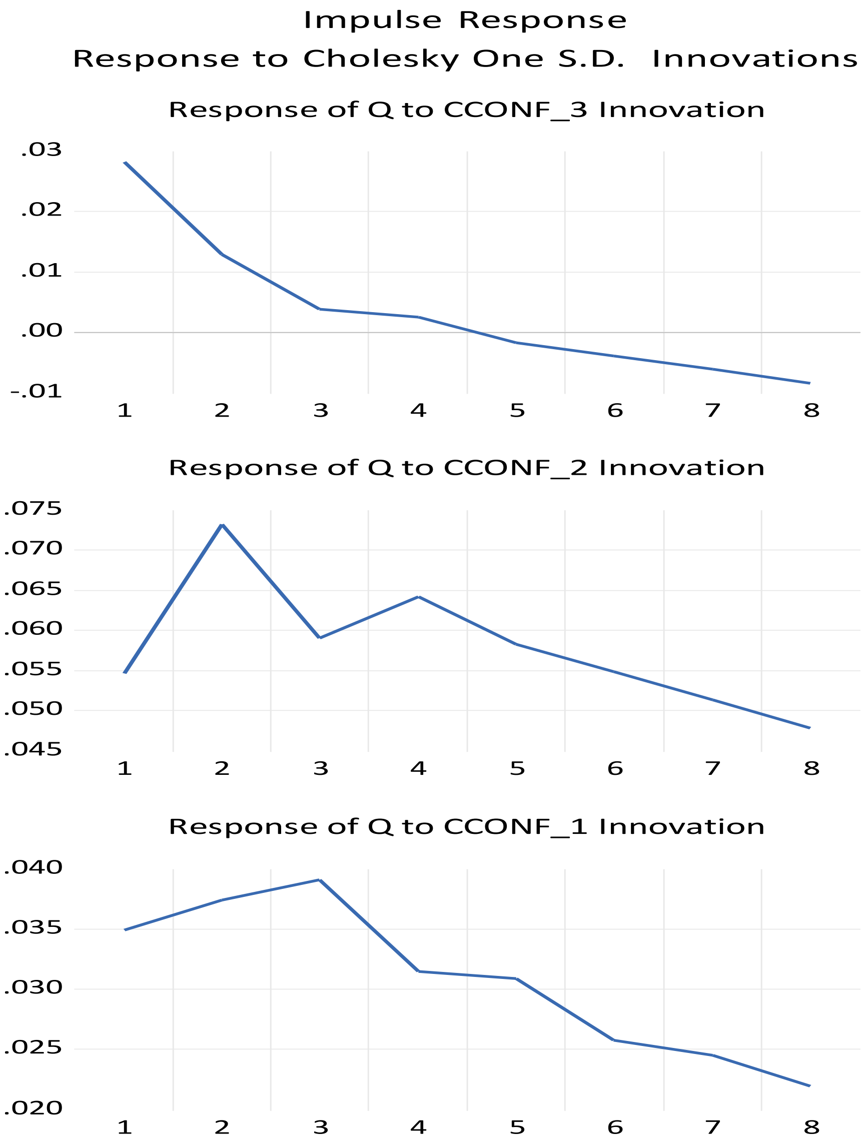
Sandmo, A. (1971). On the theory of the competitive firm under price uncertainty. The American Economic Review, 65-73.

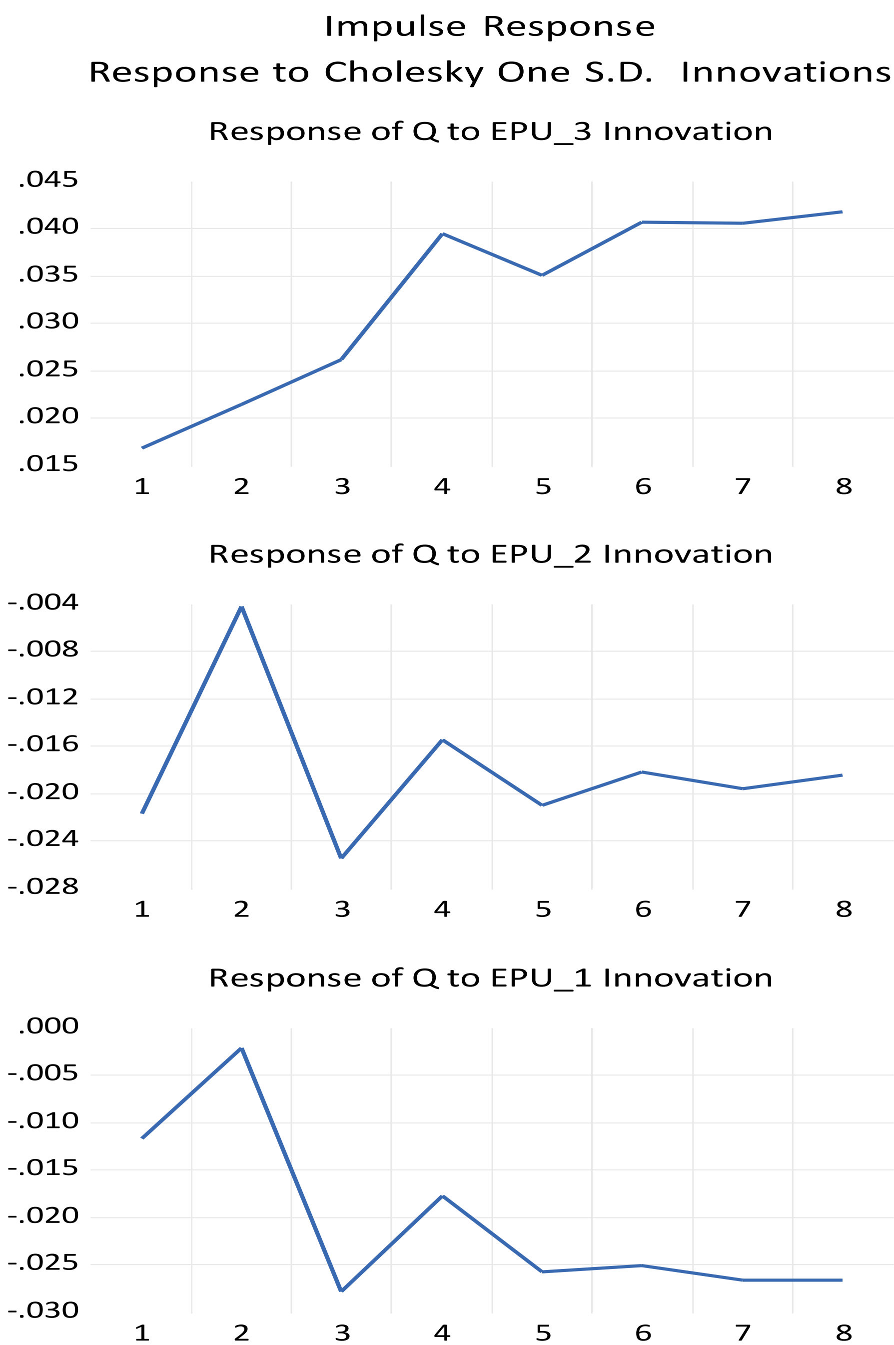
Syaifulhaq, M. D. H., & Herwany, A. (2020). Capital Structure and Firm’s Growth in Relations to Firm Value at Oil and Gas Companies Listed in Indonesia Stock Exchange. Journal of Accounting Auditing and Business-Vol, 3(1).

Yildiz Savas, E., & Kapusuzoglu, A. (2020). Risk management activities for oil and gas producers and the impact on firm value. Environmental Science and Pollution Research, 27(7), 7087-7095.

Yu, K. L. (2003). Quantile regression: Applications and current research areas. ournal of the Royal Statistical Society.

Figure 1: Impulse Responses of the Tobin's Q to Shocks to Macroeconomic Economic Uncertainty




Impulse Response
Response to Cholesky One S.D. Innovations
Response of Q to EPU_3 Innovation
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.040
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1 2 3 4 5 6 7 8
Response of Q to EPU_2 Innovation
-.004
-.008
-.012
-.016
-.020
-.024
-.028
1 2 3 4 5 6 7 8
Response of Q to EPU_1 Innovation
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-.005
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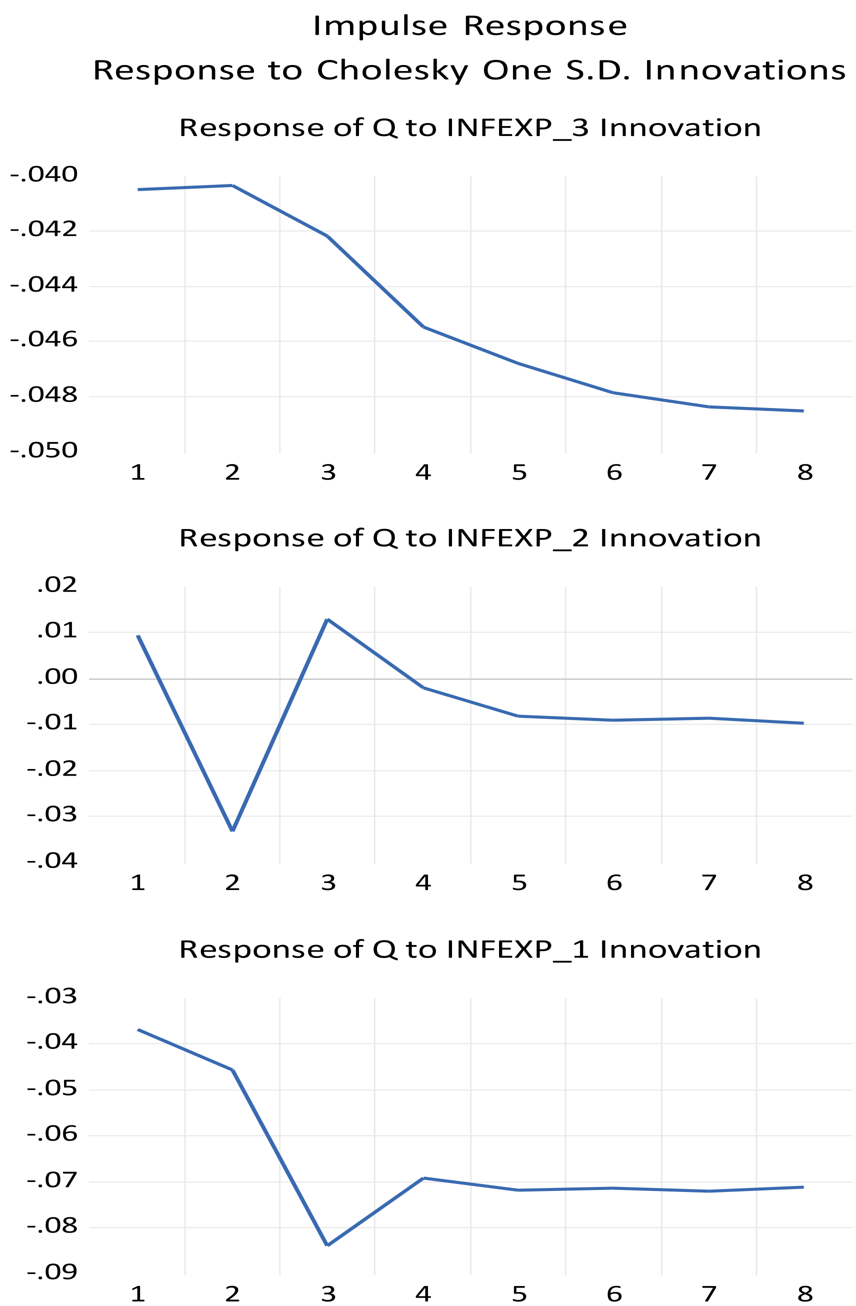
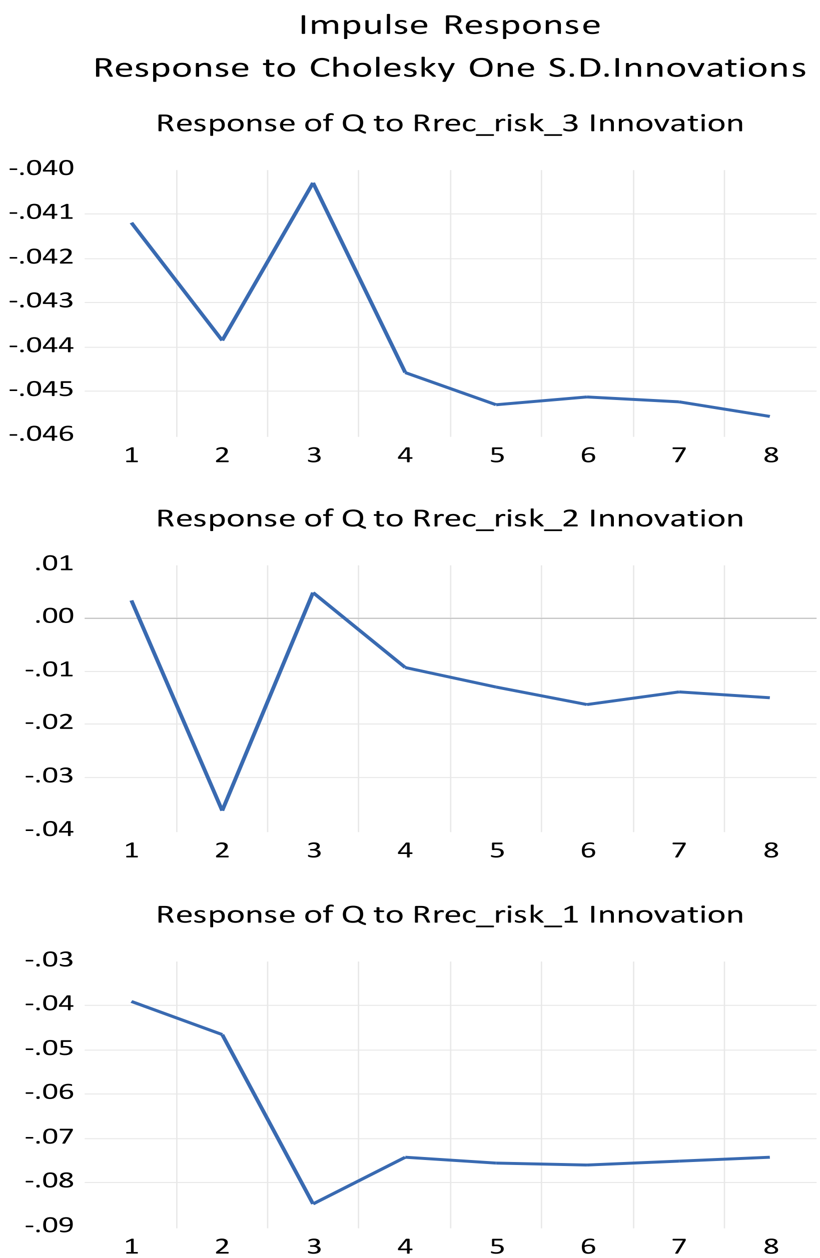
-.025
-.030
1 2 3 4 5 6 7 8


Impulse Response
Response to Cholesky One S.D. Innovations
Response of Q to INFEXP_3 Innovation
-.040
-.042
-.044
-.046
-.048
-.050
1 2 3 4 5 6 7 8
Response of Q to INFEXP_2 Innovation
.02
.01
.00
-.01
-.02
-.03
-.04
1 2 3 4 5 6 7 8
Response of Q to INFEXP_1 Innovation
-.03
-.04
-.05
-.06
-.07
-.08
-.09
1 2 3 4 5 6 7 8



Notes: Impulse responses are derived from a Panel MIDAS-VAR of order 2 based on the optimum Akaike AIC, and Schwarz SC .