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Unpacking Economic Uncertainty — Measuring the Firm, Sector and Aggregate Components

Abstract

We introduce a novel method for measuring economic uncertainty at the firm, sector, and aggregate levels using sales volatility and validate it by comparison with existing macroeconomic uncertainty measures. We use Compustat firms data in the period 2000-2022 to construct our uncertainty measures for the U.S. economy. Our findings highlight that 1) macroeconomic conditions are the predominant source of firms' uncertainty, 2) diverse firm traits yield notable heterogeneity, and 3) the manufacturing sector exhibits the highest uncertainty among sectors. Our findings shed light on the importance of firm and sectoral heterogeneity in studying uncertainty and its effects on economic activity.

JEL-Codes: D800, D220, E320, L110, L250.

Keywords: measuring uncertainty, firm heterogeneity, balance sheet data, business fluctuations.

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The resulted uncertainty measures for the U.S. economy (at the aggregate and sector level) are available at siamohades.com

1 Introduction

Economic uncertainty is a pervasive phenomenon that has significant implications for macroeconomic theory and firms' decisions. Such importance has been evidenced by its increased salience following major economic events, for instance, the Great Recession and the COVID-19 pandemic. In these recent large events, uncertainty has been shown to be both a symptom and a potential driving force of economic turmoil (Bloom, 2009; Alfaro, Bloom and Lin, 2023). From a microeconomic point of view, economic uncertainty affects firms' decisions through several channels with substantial macroeconomic effects (Bloom et al., 2018; Kumar, Gorodnichenko and Coibion, 2023; Bianchi, Kung and Tirskikh, 2023).

Firms' decisions on inputs and production rely heavily on their expectations of future sales, which are informed by past sales and inventory dynamics. These decisions are often irreversible or subject to high adjustment costs, which can lead to significant deadweight losses if made incorrectly. However, forming accurate expectations is difficult - and the resulting uncertainty can be just as costly as adjustment costs or irreversibility losses. In uncertain times, firms struggle to form precise expectations of future sales, causing delays or reductions in investment and hiring. This inefficiency can lead to significant macroeconomic slumps[1].

Additionally, uncertainty levels and dynamics need not be identical across firms and sectors. For instance, the closure of mines and industries in China during the COVID outbreak impacted the manufacturing and mining sectors globally, while services were left unaffected (Ozili and Arun, 2023). This underscores the significance of complexity and diverse pathways through which uncertainty can escalate and influence the business environment.

Economic uncertainty is multifaceted, as various factors, including changes in government policies, global economic events, natural disasters, and technological progress can cause it. From a firm's perspective, uncertainty rooted in aggregate, sectoral and firm conditions requires fundamentally different decisions to buffer against. Furthermore, economic uncertainty is a complex phenomenon because it can arise from "risk", "ambiguity" or " model misspecification" (Cagetti et al., 2015; Hansen and Sargent, 2021)[2]. For example, media coverage and public sentiment regarding a large event can influence economic uncertainty, impacting consumer behaviour and investment decisions even further. Finally, a firm might be impacted by a large economic (or policy) event in two different ways. On the one hand, the exposure to the event may be heterogeneous (different impacts on the firm's demand and or/and production). On the other hand, the perception of the event might also differ (i.e. the firm's perception of the extent of uncertainty itself – the uncertainty of uncertainty).

Existing measures of uncertainty are often based on aggregate data, such as media coverage (Baker, Bloom and Davis, 2016) and macroeconomic variables (Jurado, Ludvigson and Ng, 2015) and often fail to capture the complexity and heterogeneity of firms' salient uncertainty. Even though there have been efforts to provide disaggregated uncertainty measures, the economic literature on the impact of uncertainty on firms' decisions has mainly focused on aggregated uncertainty by assuming an identical uncertainty process for all firms, for instance, Bloom, Bond and van Reenen (2007).

We account for uncertainty heterogeneity across sectors and firms by decomposing firms' sales volatility into a multi-layered system of indices: a part that roots in commonalities of all firms (potentially macro-level developments such as economic policy and aggregated demand shocks), a part that originates in sectoral commonalities (for instance through supply chain disruptions, technological shocks and input prices) and finally a part that is specific to each firm through its decisions and activities, which ideally should be the idiosyncratic portion of uncertainty. We use each layer to reveal differences across firms in the role of macroeconomic, sectoral and firm-level sources of uncertainty and exploit time and cross-sectional variations in the different measures. Therefore, our research question can be summarised as "How is firm uncertainty decomposed into firm, sector and aggregate sources? To what extent does heterogeneity of uncertainty exist across firms?"

[1]For more details, please refer to Bloom (2009); Dixit, Dixit and Pindyck (1994)

[2]This concerns the nature of production and consumption activities - for instance, supply chain developments, change of habits and consumers' taste, etc.

Our methodology consists of first calculating the volatility of firms' sales or "Overall Uncertainty" (OU).[3] We then identify the proportion of uncertainty specific to firms by controlling for firms' core characteristics. The sector-level uncertainty is then calculated by controlling for a common factor in each sector and computed by using firms' balance sheet data to capture the commonality of firms within each sector. The weighted remainder of overall uncertainty determines the aggregate uncertainty after the firm and sector-level uncertainty components have been identified and deducted. We validate our approach by showing how our computed aggregate level uncertainty is consistent with existing measures of macroeconomic uncertainty in capturing major economic events such as the Great Recession and the COVID outbreak for the U.S. economy.

To our knowledge, we are the first to use a single disaggregated firm-level data source to construct different measures of uncertainty at aggregate, sectoral, and firm levels jointly. Our approach essentially proposes a measure that is as good as the widely used and accepted measures of uncertainty in highlighting the macro-level uncertainty among firms (Baker, Bloom and Davis, 2016; Jurado, Ludvigson and Ng, 2015) while relying on an accessible dataset. The resulting measures can describe the commonalities of uncertainty among firms and sectors and uncover sources of uncertainty heterogeneity by relaxing the assumption of a common uncertainty process for all. This approach is robust to the issues associated with measuring uncertainty from the unpredictable component of the sales process - such as heteroscedasticity caused by the high persistence of firms' sales. While we apply our method to the firms present in the Quarterly Compustat database in the United States, it can be easily applied to any other firm-level database.

Our measures of aggregate and sectoral uncertainty are counter-cyclical and reveal that most firms' uncertainty primarily originates in macroeconomic conditions. However, substantial heterogeneity in uncertainty exists among firms based on their characteristics and sectors, as noted by Born and Pfeifer (2021). Larger firms experience lower uncertainty than their smaller counterparts, while firms' age exhibits differences primarily in decomposition rather than uncertainty levels. Notably, the manufacturing sector faces higher uncertainty than the services and mining sectors, as noted in Parast and Subramanian (2021). These results hold significant lessons for policymakers and the academic literature on uncertainty and firm performance. Policymakers should be aware of smaller and younger firms' vulnerability to macroeconomic conditions, established even within a predominantly large firm sample in our paper. This underscores the impact of fiscal and monetary policies on firms' uncertainty, performance, investment decisions, and hiring choices. Moreover, our findings align with the empirical findings on the stagnation of the manufacturing sector in the U.S. economy over recent decades. Lastly, our method and results contribute to the academic literature by introducing the concept of uncertainty heterogeneity, which sheds light on the varying impacts of uncertainty on firms and sectors.

Our paper is structured as follows: Section 2 briefly reviews existing methods for measuring economic uncertainty. We then describe our dataset in Section 3, and the application of our approach to such data is explored in detail in Section 4. Section 5 demonstrates the evolution of uncertainty over time and documents our validation approach. Section 6 continues by studying the decomposition of uncertainty and exploring the heterogeneity of uncertainty. In Section 7, we provide a series of robustness checks. Section 8 concludes.

2 Literature Review

This section discusses several economic uncertainty measures and points out how our approach contributes original insight by tackling the complexity of uncertainty. These approaches mainly differ by the information source used, i.e., aggregate, survey, text-based or firm-level data.[4]

The economic literature has used aggregate data to compute uncertainty. Baum et al. (2006) constructed four simple proxies for macroeconomic uncertainty using the conditional variances of real GDP, industrial production

[3] The literature has extensively discussed the importance of firms' volatility as an indicator of economic uncertainty (Bloom et al., 2018; Comin and Philippon, 2005). We use firms' sales volatility and Overall Uncertainty interchangeably in this paper

[4] A more comprehensive review of the standard measurements of uncertainty and their empirical considerations is provided by Cascaldi-Garcia et al. (2023).

index, CPI inflation rate and returns on the S&P 500 stock-market index. In the same line, Bloom, Bond and van Reenen (2007); Bloom (2009) used share price volatility as an empirical proxy for uncertainty, justified by its positive correlation with the underlying (theoretical) standard deviation of demand shocks, real sales growth volatility and the cross-sectional distribution of financial analysts' forecasts.

Differently, Jurado, Ludvigson and Ng (2015) (henceforth JLN) argued that the volatility in one or few macro indicators or policy uncertainty does not fully represent macroeconomic uncertainty, or "what matters for economic decision-making is not whether particular economic indicators have become more or less variable or dispersed per se, but rather whether the economy has become more or less predictable, that is, less or more uncertain" (Jurado, Ludvigson and Ng, 2015, p. 1178). Their method consists of constructing a large dataset of macroeconomic and financial indicators that constitute as much information as possible to build conditional expectations of each variable in $t-1$.[5] Although their method and generated series became a widely used standard for the U.S. economy, the difficulty of the method, its data hunger and its inability to provide disintegrated or heterogeneous uncertainty prevented a wide replication across other economies. Rossi and Sekhposyan (2015) built on the same idea as JLN but relied on the unconditional likelihood of the observed outcome. Their proposed index is the percentile in the historical distribution of forecast errors associated with the realised forecast error at each date. This approach compares the realised forecast error of a macroeconomic variable of interest with its historical forecast error distribution. A realisation at the right (left) tail of the distribution hints at high "good" ("bad") uncertainty since it was difficult to predict conditionally on the information.

Another group of studies have built uncertainty measures using surveys. D'Amico and Orphanides (2008) used the probabilistic responses from the Survey of Professional Forecasters to construct their uncertainty measure for the U.S. economy. Similarly, Kozeniauskas, Orlik and Veldkamp (2018) used a macro uncertainty measure equal to the conditional variance of GDP growth forecasts for all agents in their model. Similar to aggregated data, one can measure ex-ante firms' uncertainty using managers' future expectations. For instance, Bachmann, Elstner and Sims (2013); Bachmann et al. (2021) used survey expectations data of manufacturing firms' managers to construct empirical proxies for time-varying business-level uncertainty. Awano et al. (2018) used firms' expectations of their own future turnover growth, their expectations of UK GDP growth for 2018 and the uncertainty around these expectations to measure firm-level uncertainty for a sample of UK businesses. Altig et al. (2019) elicited subjective probability distributions from business executives about their firm outcomes at a one-year look-ahead horizon.[6] The primary issue with these methods is that they are based on surveys that might reflect differences in opinions and not uncertainty per se, or be impacted strongly by managers' pessimism or optimism.

A different approach relies on text-analysis methods to identify highly uncertain times using relevant terms. Baker, Bloom and Davis (2016) provided a text-based economic policy uncertainty index (EPU), which counts the frequency of articles containing the words "uncertain or uncertainty" and "economy or economics" in the leading media of more than 25 countries.[7] Uncertainty at the political level can also affect firms' investments and performance as shown by Azzimonti (2018). Using the quarterly Economist Intelligence Unit country reports, Ahir, Bloom and Furceri (2022) constructed a World Uncertainty Index (WUI) for an unbalanced panel of 143 individual countries every quarter from 1952 based on the frequency of the word "uncertainty".

Volatility has been used as a reliable uncertainty proxy applied not just to aggregate data but also to firms'

[5]Using a FAVAR model, they then estimate the conditional expectation for any given macroeconomic variable (of N total indicators) for the h-step ahead forecast-error estimation. A weighted average of these N macroeconomic indicators forecast errors constitutes a macroeconomic uncertainty index, which we call JLN throughout the text.

[6]In terms of question design, their crucial innovation is to let survey respondents freely select support points and probabilities in five-point distributions over future sales growth, employment, and investment. Their result - called Survey Business Uncertainty - is calculated monthly for a sample of the U.S. firms and is available online **here**

[7]The EPU index has been used excessively as a policy uncertainty measure. For instance, Gulen and Ion (2016) discovered a robust negative relationship between firm-level capital investment and the aggregate level of uncertainty associated with future policy and regulatory outcomes. A complete library of EPU indices for multiple countries is available here: `https://www.policyuncertainty.com/`.

output dispersion. Firms struggle to foresee future sales during high uncertainty periods due to unforeseen economic shifts or unpredictable idiosyncratic shocks. De Veirman and Levin (2018) derived a measure of firm-specific volatility in sales from firms' balance sheet data. Baum et al. (2006) utilised the cross-sectional dispersion of firms' cash-to-asset ratios as a proxy for firms' uncertainty. Bloom et al. (2018) used the firm-level TFP dispersion to measure microeconomic uncertainty, building on Panousi and Papanikolaou (2012) in using the shocks to firms' production function as firm-level uncertainty. Comin and Philippon (2005) used the standard deviation of the annual growth rate, an approach followed similarly later by Kozeniauskas, Orlik and Veldkamp (2018). Our work builds on this method and disentangles different sources of uncertainty firms face through different levels.

Existing uncertainty measurements rely on ex-ante or ex-post differences between realised values and past conditional expectations, often using macro or aggregated data or forecasts from professional surveys. These methods offer limited insight into disaggregated sources driving uncertainty and mainly address microeconomic uncertainty. Our paper addresses this gap by quantifying and dissecting firms' volatility into three uncertainty tiers, unveiling heterogeneity among firms. Moreover, many existing measures are case-specific, with limited applicability to developing economies and potential bias from media sources. In contrast, balance-sheet firm-level data is widely available in most economies, including developing regions, making it a robust data source for measuring uncertainty in any economy.

3 Data and descriptive statistics

3.1 Data and variables

Our methodology relies on firm-level information about sales and inputs to disentangle firms' volatility into different tiers of uncertainty. We focus on implementing an analysis that constructs an uncertainty measure for the U.S. economy driven solely by firms' data. We use a sample of 24,762 publicly listed American companies registered within the U.S. borders from the quarterly dataset of Compustat between 2000Q1 and 2022Q4.

We describe below the variables used in our analysis.

Sales

We use firms' sales data since its volatility correlates largely with the business cycle, and its dispersion can capture the uncertain dynamics of the firms.[8] The cyclicality of uncertainty arises since we assume uncertainty to be time-varying following Hassler (1996). Also, Bloom (2009, 2014) found the uncertainty to be primarily counter-cyclical with respect to economic activity, indicating the importance of any uncertainty measure to be time-varying. Figure 1 shows the distribution of sales growth in normal times and during recessions. During recessions, we observe a left-ward shift of sales growth and an increase in its second moment compared to normal times. The standard deviation in recessionary times is 8% higher than normal times - which means more uncertainty about the firm's sales process. The left-ward shift during recessions also results in negative average of sales growth.

[8] Bloom et al. (2018) used TFP dispersion as an uncertainty proxy. While TFP captures the technological shocks, it cannot capture the components of volatility rooted in technology-unrelated dynamics.

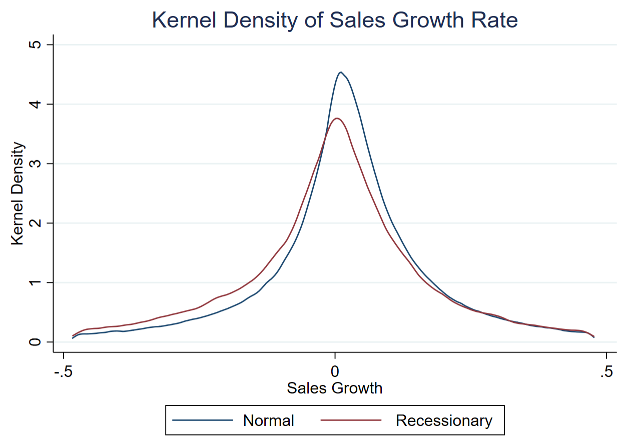


Figure 1: The Distribution of Firms' Sales in Recessionary and Normal (Non-Recessionary) Times.

Control variables and heterogeneity tiers

Our analyses use size, measured as total assets, age[9] and capital intensity to capture the largest variation of sales without multicollinearity (Herskovic et al., 2016, 2020; Uzeda, Tuzcuoglu and Castelnuovo, 2022). Firms' performance, decisions and sensitivity to business cycles depend on their size and age Clymo and Rozsypal (2022). Smaller firms usually hold fewer assets, exposing them to low diversification and lower buffer (Aivazian, Rahaman and Zhou, 2019; Liang and Rhoades, 1991). Young firms have shorter track records, smaller customer bases, and less established reputations, making them more vulnerable to market fluctuations, shifts in consumer demand, and regulation changes Comin and Mulani (2006). They also have higher growth potential and may be more aggressive in pursuing new business opportunities, which can result in greater sales volatility. Moreover, young and small firms typically have less diversified product lines and revenue streams, which makes them more exposed to external shocks (Comin and Philippon, 2005). Additional control variables in our analysis include cash flow, market value, total liabilities, and total revenue. From those, we compute the commonality among sectors and the capital intensity as the ratio between total assets and total revenues.

Our analyses then focus on the size and age to provide more insights regarding firms' heterogeneity in uncertainty. Based on firms' total asset holdings, we divide firms into four groups: very large, large, small and very small, based on the quantile of average asset holdings at each data point. In principle, we define very large and very small firms as above the 90th and under the 10th percentile, respectively. Small firms are those under the 25th percentile. Larger firms are then those larger than the 75th percentile. (see Figure 13 in Appendix A.1). The second heterogeneity tier of interest is the firms' age. At each date, firms are regrouped in their correct subgroup based on the quartile they fall into. However, there might be a learning process for the firms that survive the entire time window and the market structure issues. Some young firms might not survive and leave the sample, or old firms with a large information set from the pre-sample period use their large information set against uncertainty as a buffer. We divide the distribution at each point into young and old firms and then average the values regardless of the firms entering or exiting. In this manner, we lose less information on the market dynamics than if we were to divide the sample into young and old from a whole distribution point of view. Figure 14 in Appendix A.1 displays the average age of the firms in our sample with a logarithmic-quadratic fit to the values over time.

[9] We can only construct this variable for the listed firms based on their Initial Public Offering (IPO) date and the observation data.

Definition of sectors

There are multiple ways to define sectors within our data, from large partitions of many firms in each cluster to those which divide into smaller partitions. We use the 3-digit NAICS classification, which divides our sample into 111 subgroups. We call each of these groups a sector. From now on, when we use the term "sector-level uncertainty", we mean the uncertainty that arises in each of these subgroups. We choose to work with smaller clusters since our sample size is large enough, and the spillover effects are assumed to be larger and transformed more quickly across 3-digit clusters than broader groups. To obtain the three main "large sectors", we re-sample our data into large sectors using 1 and 2-digit classifications of NAICS. Identifier 21 groups 1,051 firms into the mining group, 31-33 identifies the 6,844 manufacturing firms and all firms with a first-digit identifier of either 5,6,7 or 8 are clustered under services, which sums to 13,022 businesses.

In Section 5, we use two widely used economic uncertainty indices as benchmarks for evaluating our measure. EPU from Baker, Bloom and Davis (2016) was then averaged in each quarter to generate a quarterly index. The JLN by Jurado, Ludvigson and Ng (2015) was readily available in the quarterly format. In addition and to answer questions regarding the potential drivers of uncertainty in the manufacturing sector, we use the ISM Supplier Delivery Index, which is available in a monthly format and we averaged these values in each quarter to have a comparable index with respect to the rest of our analysis.

Finally, recessions are defined via NBER recession bands for quarterly time series.

3.2 Descriptive statistics

Below, we provide the descriptive statistics of our main variables of interest that enter our analysis in the log-transformed format. The log transform's rationale is to reduce the skewness of the firm-level variables and reduce the issues that might arise in a dynamic panel estimation due to autocorrelation. It also becomes evident that the coverage of the Quarterly Compustat dataset is much broader among the listed firms. Once we control for these listed firm-specific variables, our estimations will be conducted among smaller samples.

Variable (in log)	Content	Observations	Mean	SE	Range
S	Sales	623,149	3.85	2.82	-6.90 - 12.24
CH	Cash Flow	367,610	3.21	2.98	-6.91 - 12.57
TA	Total Assets	652,188	5.70	3.05	-6.90 - 15.27
MV	Market Value	381,917	5.60	2.56	-9.21 - 14.88
LT	Total Liabilities	653,089	5.05	3.12	-6.91 - 15.25
TR	Total Revenue	559,900	3.91	2.90	-6.91 - 12.24
LI	Long-Term Investments	208,135	3.71	3.34	-6.90 - 14.53
Computed Variables					
Age (log)	Quarter - IPO	350,868	1.97	1.11	-5.90 - 4.30
Cash Flow / Total Assets	CH / TA	372,743	0.18	0.23	-1.37 - 1.10

Table 3.1: Firm-Level Variables Descriptives.

Source: Compustat database in Quarterly frequency for 2000Q1-2022Q4. Geographical coverage includes firms registered in the United States and filed in the Compustat database.

4 Methods: measuring economic uncertainty

4.1 Conceptual approach

We begin by improving the approach applied to the firm-level data in Comin and Philippon (2005) and Bloom et al. (2018).Our method calculates firms' volatility as an observation outside of firms' "comfort zone". Hence, it does not differentiate the right and left-tail events, as illustrated in Figure 2:

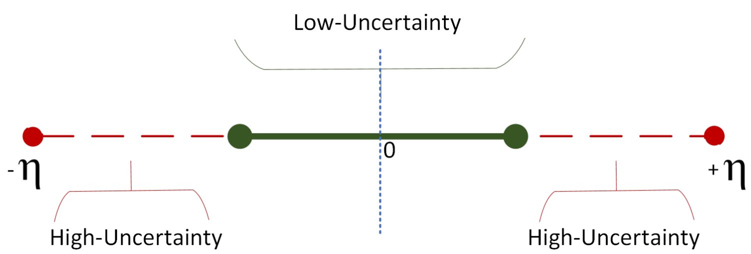


Figure 2: Firms' comfort and discomfort ranges of performance.

These tail events show up as large residuals on an empirical model that explains conventional variation in firms' performance. Our measure of uncertainty is a variation of cross-sectional dispersion of firms' sales defined as the cross-sectional dispersion of the unpredictable component embedded in data as in Uzeda, Tuzcuoglu and Castelnuovo (2022) and Bloom et al. (2018)[10]. It uses residual volatility as a proxy for uncertainty, as the cross-sectional dispersion corresponds to the unexplained variations by the model and control variables added in each computation. We then disentangle different tiers of uncertainty and identify the portion of sales uncertainty specific to each firm, sector or aggregate-level source.

We start from a measure of Overall Uncertainty (OU). It is defined to reflect the sales volatility without imposing any firm or sector-characteristic controls. It captures all the predictable and unpredictable components of uncertainty. Next, we will add a series of controls in order to manipulate the variations in sources of uncertainty.

OU is measured as the cross-sectional dispersion of shocks (i.e. residuals) $\varepsilon_{i,t}$ to the firm's net sales at time t compared to the firm's average $\bar{\varepsilon_i}$:

$$OU_{i,t} = \frac{(\varepsilon_{i,t} - \bar{\varepsilon_i})^2}{T-1} \tag{1}$$

where the residual $\varepsilon_{i,t}$ is obtained from an AR(1) of firms' sales with fixed effects:

$$log(S_{i,t}) = \rho log(S_{i,t-1}) + \lambda_t + \mu_i + \varepsilon_{i,t} \tag{2}$$

Where $S_{i,t}$ denotes the firm i's log of sales, μ_i is the firm-fixed effect to control for unobservable firm characteristics, and λ_t is the time-fixed effect to control for cyclical shocks. The OU measure introduced above is a weighted sum of uncertainty in three different levels: 1) aggregate Level Uncertainty (ALU), 2) weighted within-sector sectoral uncertainty (SLU), and 3) weighted across all firms firm-level Uncertainty (FLU).

$$\mathrm{OU}_{i,t} = \mathrm{ALU}_{i,t} + \omega_{1,i,t}\mathrm{SLU}_{i,t} + \omega_{2,i,t}\mathrm{FLU}_{i,t} \tag{3}$$

[10]Their index measures an "overall-level" uncertainty from technological progress captured by TFP, independent of firms' or sectors' characteristics. Hence, with their measure, it is impossible to track and identify the sources of changes in uncertainty and identify the sector, aggregate or firm-specific sources of uncertainty.

where the weights $\omega_{1,I,t}$ and $\omega_{2,I,t}$ represent the firm-level and sector-level shares of sales in the total sample respectively (see also equation 12). Such deconstruction of OU can be represented graphically as shown below:

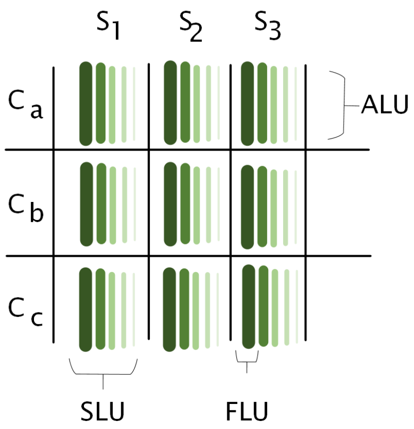


Figure 3: Tiers of uncertainty faced by firms in countries a,b,c and in sectors 1,2,3.

In each step of our construction, we add a set of appropriate controls from firms' data so that the residuals can be used as a tool for uncertainty measurement and identify either ALU, SLU, or FLU. We proceed by estimating two of these components (FLU and SLU), while the third element (i.e ALU) is computed as the remainder of OU after these two components have been controlled for.

The equation below shows an application of Equation 2 with a set of controls $X_{i,t}$:

$$y_{i,t} \equiv log(S_{i,t}) = \rho log(S_{i,t-1}) + \mu_i + \lambda_t + X_{i,t}\boldsymbol{\beta} + \varepsilon_{i,t} \tag{4}$$

Where the conditional expectation $\mathbb{E}_t\left(y_{i,t}\right) = \rho log(S_{i,t-1}) + X_{i,t}\boldsymbol{\beta}$ provides an optimal prediction based on the Mean Squared Error (MSE) for the $M \times 1$ vector $y_{i,t}$ containing a set of firm-balanced sheet information with observations going from $t = 1$ to T, where M identifies the number of independent variables of interest, and T the time-series dimension or the number of quarters in our case. Therefore, the response variable's unpredictability (and uncertainty) is associated with the error term $\varepsilon_{i,t}$.

To identify the economic uncertainty from the residuals of regression Equation 4 above, we need to choose a set of variables in $X_{i,t}$ that explain a considerable variation in the dependent variable $y_{i,t}$. To ensure that the error term $\varepsilon_{i,t}$ in Equation 4 is roughly unpredictable in each uncertainty measure, we define $X_{i,t}$ - the vector of independent variables and controls - in a way that extracts as much predictable component of firms' volatility as possible from the dependent variable - sales in our case (see also Comin and Philippon, 2005). We use combinations of fixed effects and control variables depending on the desired tier of uncertainty in each step. Note that our estimation approach for the dynamic panel (as justified below) implies the automatic use of panel-fixed effects. Table 4.1 below displays the set of control variables added to the $X_{i,t}$ matrix for estimating each level of uncertainty.

Measure	Time FE	Firm FE	Controls
OU	✓	✓	-
FLU	✓	✓	Age, Size & Capital Intensity
SLU	✓	✓	Sectors' Common Factors
ALU	The Residual as ALU = OU - FLU - SLU		

Table 4.1: Control variables and fixed effects in estimating each uncertainty level.

4.2 Firm-Level Uncertainty (FLU)

To identify the firm-level sources of uncertainty hidden and embodied in OU, we add firm-characteristic controls to our regression above and construct our preliminary FLU index in the same fashion as OU.

$$log(S_{i,t}) = \rho log(S_{i,t-1}) + \lambda_t + \mu_i + \sum_{c=1}^{C} \beta_c X_{i,t} + \varepsilon_{i,t} \tag{5}$$

$$FLU_{i,t} = \frac{(\varepsilon_{i,t} - \bar{\varepsilon_i})^2}{T-1} \tag{6}$$

The set of controls in X contains capital intensity, firm age and firm size., guided by the previous literature. Herskovic et al. (2020) found that large firms are less volatile than their smaller counterparts because they are connected to more customers, improving the diversification of their client portfolio.[11] We also consider firm age as the younger firms are more prone to experiencing firm relevant-business-conditions uncertainty such as down-sizing, CEO change and being bought out or listed. In turn, capital intensity displays a strong positive correlation with uncertainty: the accumulation of assets does not necessarily provide a buffer for firms regarding their volatility or uncontrolled firm uncertainty.

4.3 Sector-Level Uncertainty (SLU)

According to Uzeda, Tuzcuoglu and Castelnuovo (2022), to measure sector-level uncertainty, one needs to estimate uncertainty at different layers of economic data and then model a large dataset to pin down all the implications that various economic system dimensions may have on uncertainty. In that case, sectoral uncertainty is viewed as a dynamic factor common to the time-varying volatility of a subset of variables corresponding to a particular sector. To pin down SLU, we repeat our previous process, but instead of controlling for firms' characteristics, we add a sectoral common factor ($CFact_{i,t}$) as a control. We propose to use a common factor among firms in each sector, similar to Barigozzi et al. (2014); Herskovic et al. (2020) as well as Jurado, Ludvigson and Ng (2015), to capture the sector-relevant variation. This allows us to include a sector-related control variable that comes from the heart of our initial dataset and not external or aggregated vintages of firms' data.

$$log(S_{i,t}) = \rho log(S_{i,t-1}) + \lambda_t + \mu_i + CFact_{i,t} + \varepsilon_{i,t} \tag{7}$$

Where again $S_{i,t}$ denotes the firm i's sales, μ_i is the firm fixed effect, and λ_t is the time fixed effect. We then define the sector-level uncertainty as the cross-sectional dispersion of the residuals of the regression above:

$$SLU_{i,t} = \frac{(\varepsilon_{i,t} - \bar{\varepsilon_i})^2}{T-1} \tag{8}$$

In Figure 4, we show the construction of each sector's common factor and how the data on firms in these subgroups can be used to construct one single variable summarising the most important information of firms in that sector.

[11] It also implies that not only do small firms have higher uncertainty, but they also face higher uncertainty of uncertainty (larger second moment of uncertainty).

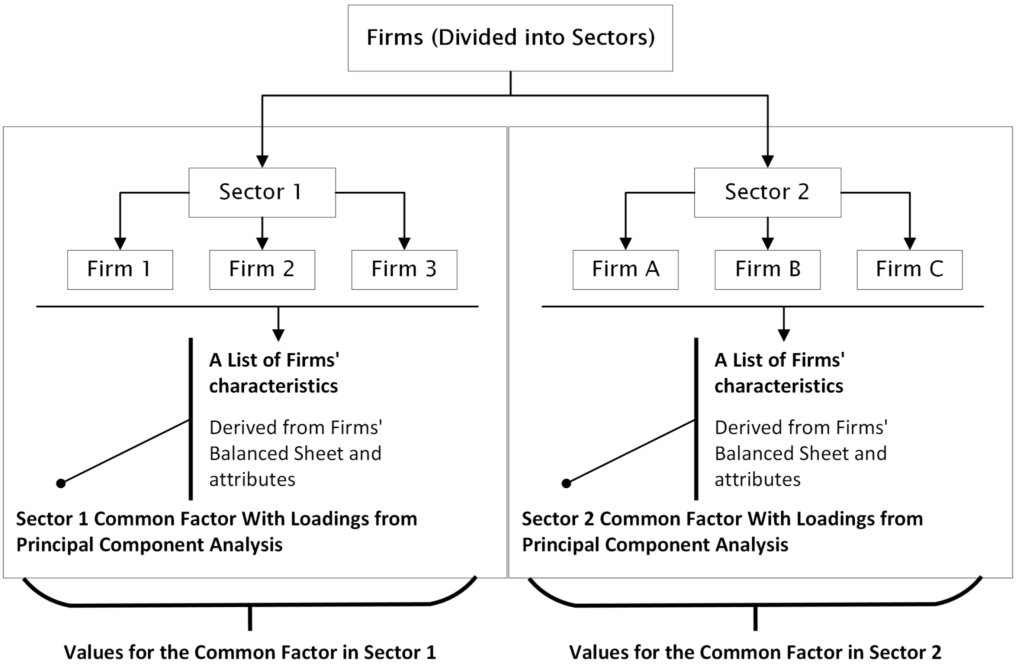


Figure 4: The Commonality of Firms' Characteristics into One Common Factor Variable for Each Sector.

We apply the dynamic factors approach (Stock and Watson, 2011) to summarise firms' data into one component that explains the co-movement and covariation in that data-rich environment. With this variable combined with fixed effects, the isolated variation in uncertainty can be associated with sector-specific uncertainty that affects firms' sales. The common factor has the structure:

$$\text{Common Factor} \equiv CFact_{i,t} = \Lambda_j^{F'} \mathbf{F}_{i,t} \tag{9}$$

where $\mathbf{F}_t$ is an $r_F \times 1$ vector of latent common factors and Λ_j^F is a corresponding $r_F \times 1$ vector of latent factor loadings. The $CFact_{i,t}$ variable is then the common factor determining uncertainty between the firms in each sector j at time t. The factor loadings $\Lambda_j^{F'}$ are calculated through a principal component analysis - following McCracken and Ng (2015) and Ma and Samaniego (2019). In this method, the number of factors that represent the firms' commonality in each sector is decided based on the eigenvalue criterion. A natural question at this point may arise regarding the choice of variables in constructing the sectoral common factor.

Based on a simple Bayesian-like penalising algorithm, we find that a short list of variables containing the most information is favoured. These variables must include information on the most critical aspects of the businesses and what identifies them from other businesses in other sectors. Our algorithm first constructs a common factor using all the time series for all the firms in the sector, namely $CFact^{\text{Large}}$. It then creates factors starting from an arbitrarily ordered list that maximises the following fraction:

$$\text{Correlation Criterion} = \max_N \frac{Corr\left[CFact^N, CFact^{\text{Large}}\right]}{N}$$

In other words, we maximise the correlation with the large initial factor and penalise it in each step of adding variables by the total number of series that entered the factor construction. We find that the optimal vector of variables to be included is:

$$\mathbf{F}_{i,t} = \Omega\Bigg(\text{Cash/Total Assets}, \text{Net Revenue}, \text{ Long Term Investments}, \text{Total Liabilities}, \text{Age}\Bigg)$$

The resulting common factors in sectors are calculated through principal component analyses of the data in each sector.[12] The values are then stacked into a single variable ($CFact$) and normalised so the new variable's distribution follows a $\sim (\mu = 0, \sigma = 1)$. In Figure 15 (in Appendix A.2), we show the distribution of our sectoral common factor. The values around 0 show that the firms at those points in time behave and experience close-to-average attributes in their sector. In other words, values on the right and left tails where there is higher difference with respect to zero display conditions in which the firm is experiencing extreme circumstances with respect to the expected value in its sector.

After constructing the firm-specific and time-varying common factor for each sector, we add this variable to our regression on estimating sector-level uncertainty as:

$$log(S_{i,t}) = \rho log(S_{i,t-1}) + \alpha CFact_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{10}$$

We then define the sector-level uncertainty as the cross-sectional dispersion of the residuals of the regression above:

$$SLU_{i,t} = \frac{(\varepsilon_{i,t} - \bar{\varepsilon_i})^2}{T-1} \tag{11}$$

Our specification is robust to our choice of sector size (as defined in section 3). In Section 7, we examine our method by using the 1-digit sectors in the same analysis as above, and we show that our precision in choosing such small sectors is robust to a choice of larger sectors.

4.4 Aggregate-Level Uncertainty (ALU)

So far, we have identified the firm and sector-specific components of uncertainty in our analysis. The remainder of OU, after deducting firm and sector uncertainties, is the Aggregate-Level Uncertainty (ALU), as we call ALU:

$$\text{ALU}_{i,t} = \text{OU}_{i,t} - \left(\frac{S_{i,t}}{\sum_{i=1 \in N_j}^{N_j} S_{i,t}} \right) \text{FLU}_{i,t} - \left(\frac{\sum_{i=1 \in N_j}^{N_j} S_{i,t}}{\sum_{i=1 \in N}^{N} S_{i,t}} \right) \text{SLU}_{i,t} \tag{12}$$

We define the weights for each tier as the relative sales of the firm over the sector and the sector over the whole economy tier to solve the granularity issue of uncertainty. Large firms might drive sector uncertainty, and large sectors' uncertainty might result in the uncertainty of the whole economy.

4.5 Estimation Method: Dynamic Panel using a GMM Estimator

Note that we are estimating a specific case of a dynamic panel of the form:

$$log(S_{i,t}) = \sum_{j=1}^{p} \alpha_j log(S_{i,t-j}) + \mathbf{X}_{i,t}\boldsymbol{\beta} + \mu_i + \lambda_t + \varepsilon_{it} \quad i = 1, \ldots, N \quad t = 1, \ldots, T_i \tag{13}$$

where in both Equations 5 and 10 the lagged component only consists of one lag of sales, and the matrix of controls $\mathbf{X}$ consists of observations on either firm controls (in Equation 5) or sectoral common factor (in Equation 10). The components μ_i and λ_t capture the firm and time-fixed effects, which may be correlated with the covariates. In this form, the lagged dependent variables are correlated with the unobserved panel-level effects, making standard estimators inconsistent.

We perform the Wald-test proposed by Wooldridge (2010) and find a significant pattern in heteroscedasticity of residuals in estimating OU, FLU and SLU. To solve this issue, we use the methodology developed by Arellano and Bover (1995); Blundell and Bond (1998), which uses a Generalised Method of Moments (GMM) estimator to avoid the heteroscedasticity issue. Our methodology uses the first lag of the log of sales as an instrument. In essence, lagged differences are used as instruments for the level equation in addition to the

[12] We use 111 NAICS three-digit firm clusters from both American and Canadian firms since the sector-level processes are quite common between the two countries and trade is fluid. Under these assumptions, using a larger sample is not costly.

moment conditions of lagged levels as instruments for the difference equation. The estimator in these models is robust to heteroscedasticity and provides residuals that are uncorrelated to the past-observed residuals to the econometrician. In this way, we can capture the truly unpredictable component of the sales process, independent of the uncertainty persistence from previous quarters.

4.6 Descriptive Statistics of Uncertainty

Table 4.2 presents the summary statistics for the four uncertainty measures. As shown above, these measures differ in their data requirements, which leads to a higher number of observations for overall uncertainty (OU, 17,080 firms) and the lowest number of observations for aggregate uncertainty (ALU, 4,811 firms). ALU imposes the highest level of requirements as both the controls needed to construct FLU and SLU need to be available.

Negative values of ALU might result as the nature of ALU could imply the presence of confounding factors. The negative uncertainty here is caused by factors that we either cannot observe or are out of the reach of our method. It can also be caused by having a very high share of sales in the sector or operating in a sector very large compared to the economy. In this case, the weights in Equation 12 become too large and cause negative uncertainty. However, ALU is negative only in 7% of the sample (9,561 observations). In what follows, we replace the negative values with NA for our measure to remain as a conservative (lower bound) of aggregate uncertainty.

Our method generates values of uncertainty derived from the residuals of regressions with estimations available in the Appendix C. Hence, we expect the absolute values of uncertainty measures to be very low. However, we can rescale these values by multiplying them by 100 to understand the descriptive statistics better. In Table 4.2, we report the descriptive statistics of uncertainty tiers multiplied by 100, for a sample between the 1^{st} to the 99^{th} percentiles, namely after disregarding outliers.

Measure	Mean	Std.Dev	25^{th}	50^{th}	75^{th}	Min-Max	Firms	Obs
$OU \times 100$	0.220	0.506	0.009	0.046	0.183	0.000 - 4.770	16,589	578,886
$FLU \times 100$	0.145	0.269	0.008	0.039	0.149	0.000 - 2.075	5,584	162,683
$SLU \times 100$	0.191	0.511	0.005	0.030	0.130	0.000 - 6.163	5,220	146,721
$ALU \times 100$	0.258	0.572	0.016	0.068	0.228	0.000 - 5.516	4,772	122,761

Table 4.2: The Descriptive Statistics of Uncertainty (1^{st} to 99^{th} Percentiles) - Unbalanced Sample of Uncertainty Components.

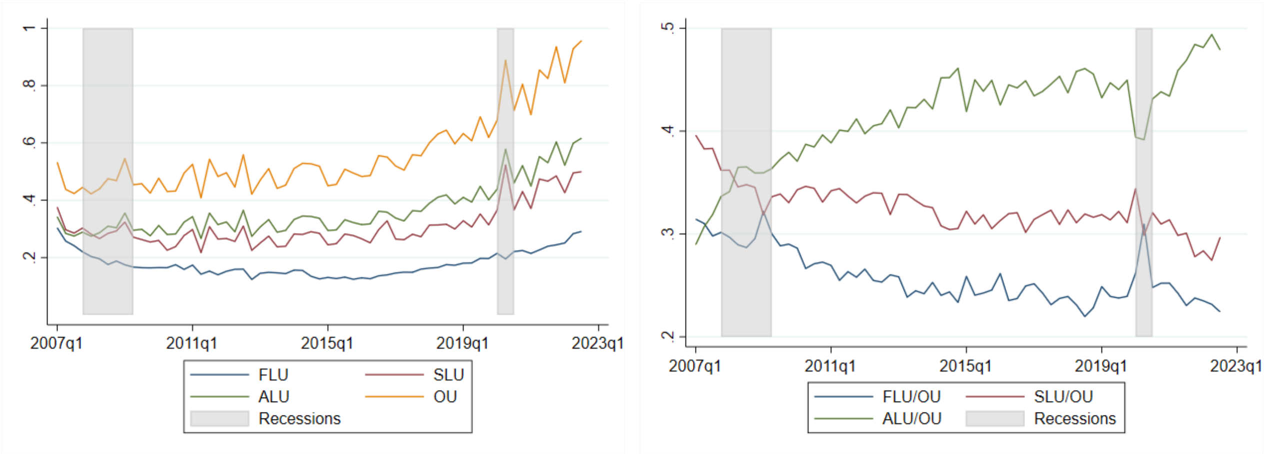
We can see that the FLU lies on a smaller range and has a lower mean than SLU and ALU. Figure 16 in Appendix A.1 reports the distribution of the four uncertainty components.

5 Validation

In this section, we validate our methodology by analysing whether our measures display expected behaviour over time and with respect to large economic events and the business cycle. We then demonstrate how closely our aggregate uncertainty measure co-moves with the existing measures of uncertainty in the literature.

5.1 Evolution of Uncertainty Over Time

We now focus on studying the evolution of different tiers of uncertainty over time. For each measure, we have obtained a value for each firm-quarter observation. For each firm for which we observe the three components (i.e. a balanced sample), we compute the relative share of FLU, SLU and ALU as part of total uncertainty (OU). In Figure 5 below, we report the cross-sectional average for each period and each measure.



(a) Averaged uncertainty components over time

(b) Averaged proportions of uncertainty over time

Figure 5: Evolution of Uncertainty Levels and Proportions.

We can see that both the Great Recession and the COVID-19 outbreak were reflected primarily in the sectoral and aggregate components of uncertainty. Furthermore, since early 2020, all uncertainty components have remained at a sharply increasing dynamic. Strikingly, the aggregate and sectoral components of uncertainty have increased since our sample began. Furthermore, over time, the aggregate uncertainty is shaping a larger proportion of firms' overall uncertainty.

Aggregate-level uncertainty reflects the overall risk of the economy, which is beyond the control of individual firms. These risks are known as systematic risks and can simultaneously affect multiple firms and sectors, such as changes in interest rates, government policies, or global economic conditions. Therefore, aggregate levels of uncertainty could remain high due to the persistent presence of these risks. Furthermore, the market structure of some industries can also contribute to higher sectoral levels of uncertainty. In competitive markets, firms may have little control over prices, and uncertainty about future demand and supply conditions could persist. In contrast, firms with market power or monopoly positions may face lower uncertainty at the firm level since they have larger control over pricing and other strategic decisions. Therefore, sectors dominated by competitive markets may experience higher levels of uncertainty.

We now focus on aggregate level uncertainty (ALU) for the U.S. economy measured through our analysis and reported in more depth in Figure 5(a). It can be compared to the business-cycle evolutions and other aggregated uncertainty measures - including sectoral and firm-levels derived in this paper. The first peak of aggregate uncertainty - in our sample - is reached during the recession of 2008-09. The next important peak was the peak in 2018, which can be attributed to the trade war tensions between China and the U.S. (IMF, 2016; Amiti, Redding and Weinstein, 2019), and reflected in the uncertainty index of Ahir, Bloom and Furceri (2022), (see Figure 12). As the resulting volatile asset prices occurred simultaneous with the mid-term elections, the American economy experienced extremely high uncertainty. Finally, the last peak of ALU reflects the COVID-19 crisis in 2020, which resulted in the highest uncertainty across our sample.

Figure 17 in Appendix A.1 provides additional information on the cross-sectional nature of uncertainty by displaying, for each measure, the confidence intervals and recession periods. We observe a local peak in aggregate uncertainty during the 2008-2009 crisis, which is then slightly topped by the high uncertainty of the trade war in 2018. We find substantial heterogeneity in the 2018 peak reflected in the wider confidence intervals of both SLU and ALU. The historical peak - as far as our sample is concerned - is the sharp increase in uncertainty in the first quarter of 2020 - due to the COVID outbreak. The period after 2020 is characterised by extremely high uncertainty, potentially due to the Russia-Ukraine war, high inflation, the expectations of an upcoming recession in 2023, and continuous supply chain disruptions.

5.2 Uncertainty and the Business Cycle

Numerous studies in the literature display a strong rise in their uncertainty measure during the recessions (Bloom, Bond and van Reenen, 2007; Jurado, Ludvigson and Ng, 2015; Baker, Bloom and Davis, 2016; Bloom et al., 2022). Whether uncertainty soars due to economic recessions or it dampens growth is still an open question due to the difficult identification of causality. Furthermore, not all uncertainty is bad, as right-tail events also are captured by our uncertainty measures. In this section, we show that our uncertainty measures behave as expected with respect to episodes of booms and recessions. We first look at the correlation between uncertainty values with aggregated sales and firm-level sales growth. We then highlight how the variance of our uncertainty measures evolves in recessionary versus non-recessionary times.

Table 5.1 shows that our aggregate uncertainty measure is strongly counter-cyclical. Sector and firm-level uncertainties are strongly counter-cyclical in the whole sample and normal times, while in recessionary periods, they demonstrate both counter and pro-cyclical behaviours:

Uncertainty and Business Cycle - Correlation

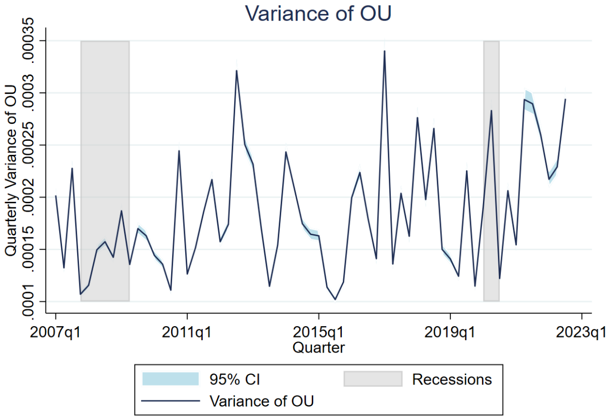
		FLU	SLU	ALU
Aggregate-Level	All Sales	-0.18***	-0.48***	-0.19***
	All Sales	0.56***	0.03***	-0.03***
	All Sales	-0.20***	-0.49***	-0.21***
Firm-Level	Sales Growth	0.00	-0.09***	-0.11***
	Sales Growth	0.00	-0.14***	-0.20***
	Sales Growth	0.01*	-0.08***	-0.10***

***:$p < 0.01$, **:p0.05 & *: $p < 0.10$

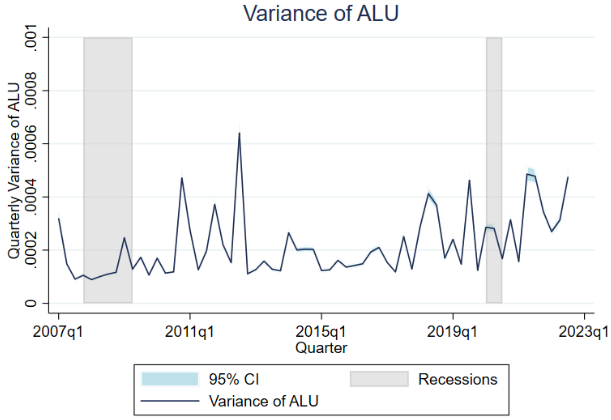
Table 5.1: Correlations of Uncertainty Components with the Sum of Sales (Aggregated) and Firm-Level Sales Growth in each Quarter, with Non-Recessionary vs Recessionary Periods.

The occasional pro-cyclicality of uncertainty is neither fully counter-intuitive nor unconventional. For example, Jurado, Ludvigson and Ng (2015)'s uncertainty measure is also pro-cyclical in normal times and counter-cyclical in recessionary times. Not only the direction of the causality between business cycles and uncertainty has remained an open question, but it is also difficult to assess business cycle features of either macro or financial uncertainty without the other. Also, not all uncertainty is bad: as also discussed in Rossi and Sekhposyan (2015), right tail events also contribute to uncertainty measures, while they are not necessarily "bad" events for the economy. In our case, we are combining right and left-tale observations of sales change as unpredictable (at least to our econometric specification) events. For instance, a change in the CEO of a company might bring about creative marketing solutions, leading to a short-term increase in sales. In this case, there is a simultaneous increase in both company's profitability and uncertainty.

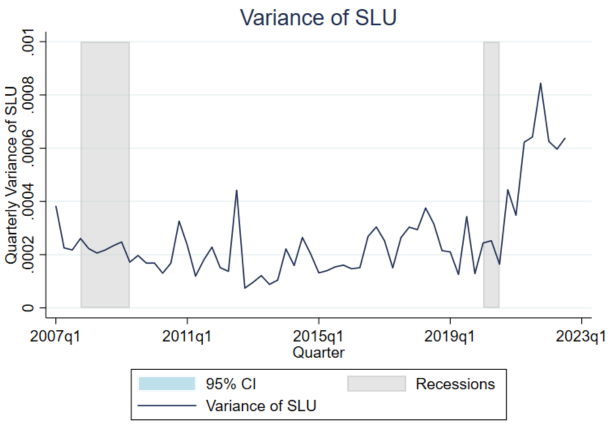
Similar to Bloom et al. (2018), we argue that uncertain periods are not only periods of higher uncertainty as reflected in the first moment of the uncertainty measure, but they also represent higher second moments of uncertainty. Ideally, we would observe a higher variance in the recessionary periods, as not only does the revenue process through sales become uncertain, but the process of uncertainty becomes uncertain. Initially, we find a positive significant correlation at the 99% confidence interval between the first and second moments of uncertainty at each tier and among each other. In turbulent periods, it is not only difficult to forecast the sales in the next period but also to understand how turbulent the economy is. The correlation slightly increases to 5% in NBER recessionary periods. In other words, uncertainty and its extent become less unpredictable when the economy performs poorly.



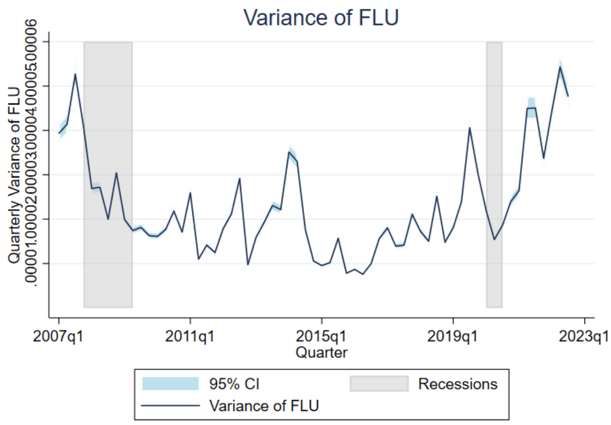
(a) Overall Uncertainty (OU)



(b) Aggregate Level Uncertainty (ALU)



(c) Sector Level Uncertainty (SLU)



(d) Firm Level Uncertainty (FLU)

Figure 6: Variance of the uncertainty measures over time

Figure 6 above reports the variance evolution in our uncertainty measures more systematically. It displays a visually persistent lagged relationship between the first and second moments of uncertainty. After the recessionary period of 2008-09, the uncertainty about uncertainty increased consistently until around 2013. The COVID outbreak reveals instead a low variance of uncertainty, as almost every sector and firm was hit severely. The quarters after the outbreak, on the other hand, have shown a higher uncertainty about the extent of uncertainty for firms - which could be explained by the politically and economically turbulent period after the COVID outbreak, hinting at how heterogeneously firms experienced uncertainty.

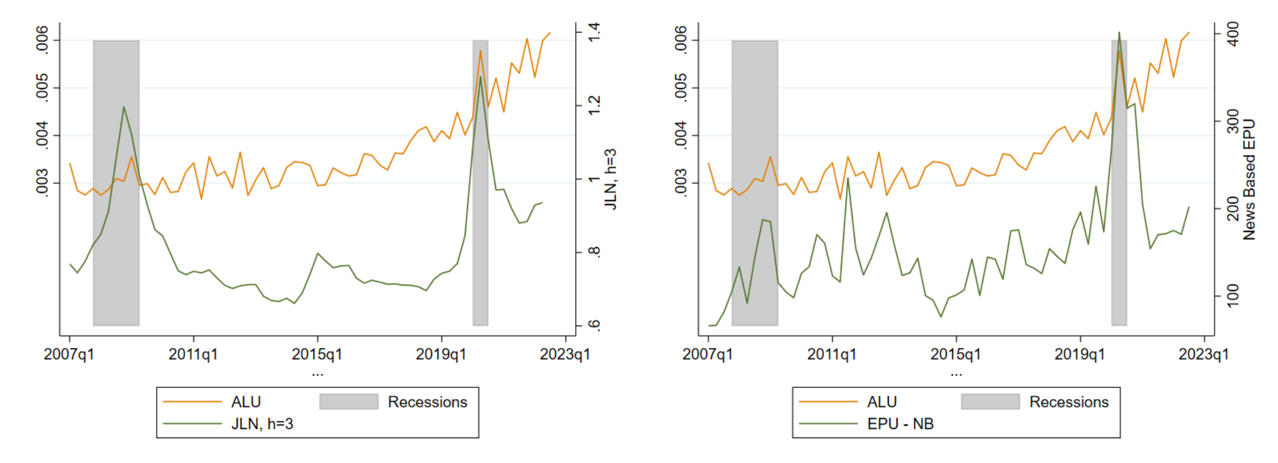
5.3 Comparison with existing measures

To validate whether our aggregate level uncertainty index corresponds to other measures of economic uncertainty, we compare it with the index from Jurado, Ludvigson and Ng (2015) (JLN) and the Economic Policy Uncertainty measure (EPU) from Baker, Bloom and Davis (2016).[13] The rationale behind our focus on validating ALU solely is the lack of a correspondent for firm and sector-level uncertainty available for us to

[13]In particular we focus on the most common versions of these indices, namely the JLN measure with 3 lags and the news-based EPU measure.

compare.

This comparison exercise is reported in Figure 7. We first observe that similar to the JLN and EPU indices, our measure captures the sharp recession of 2007-08 and does well in pointing out the sharp peak of the uncertainty of 2020. While JLN does not capture either the trade war of 2018 or other turbulent events during President Trump's administration, ALU displays a significantly higher uncertainty during the Republican government compared to President Obama's office through a positive trend starting in 2016.



(a) ALU vs. JLN

(b) ALU vs. EPU

Figure 7: The evolution of ALU over time in comparison with existing measures of uncertainty.

Furthermore, our uncertainty index is strongly correlated to the existing ones as reported in Table 5.2. One may also raise the question of whether such strong correlations are being driven by either recessionary or non-recessionary times. We differentiate those periods as defined by NBER recession bands and divide our sample in non-recessionary and recessionary times and compute the correlation values again. The second and third panels of Table 5.2 show that our measure is more strongly correlated to the commonly used uncertainty indices in the literature during the recessionary period. Interestingly, the correlation between JLN and EPU also increases during the recessionary periods and reduces largely during the moderate years. The rationale behind weaker correlation in non-recessionary periods is the nature of uncertainty that each measure is capturing - while in recessionary periods all measures agree on a rise in uncertainty.

		ALU	JLN
Overall	JLN	0.41***	
sample	EPU	0.58***	0.55***
Non-recessionary	JLN	0.58***	
periods	EPU	0.51***	0.29***
Recessionary	JLN	0.72***	
periods	EPU	0.97***	0.77***

***:$p < 0.01$, **:p0.05 & *: $p < 0.10$

Table 5.2: Correlation Table between ALU, JLN from Jurado, Ludvigson and Ng (2015) & EPU from Baker, Bloom and Davis (2016).

6 Heterogeneity of uncertainty across firms and sectors

In this section, we exploit the micro nature of our uncertainty measures to study the sources of differences in uncertainty across firms. We start by studying differences in the weight of the components in firms' overall uncertainty. Then, we study the role of two important firm characteristics, size and age, in explaining firm differences in perceiving uncertainty. Finally, we explore the role of sectoral heterogeneity.

Before exploring the details regarding heterogeneity of uncertainty, we clarify what we exactly mean by the concept of heterogeneity in uncertainty. With our measure, we are able to highlight not only the firm-level component of uncertainty but also how firms differ in the extent of sectoral and aggregate levels. Take the example of a chip-producing establishment that was immensely hit by the COVID-19 outbreak, which is reflected in aggregate uncertainty. This firm's uncertainty - both in aggregate and sectoral components - differs significantly from that of a bike saddle producer. Even though both were severely hit by a shock, their "perception" and "experience" of uncertainty were quite different. Potentially, this heterogeneity is rooted in firms' natural exposure to external shocks - especially in production and demand.

6.1 Heterogeneity in types of uncertainty across firms

So far, we have observed the evolution of uncertainty over time and some of the major properties of aggregate uncertainty. We also discussed that the macroeconomic uncertainty lies quantitatively above firm-level uncertainty in our sample time frame. Alternatively, and to confirm the idea that most of the firms' uncertainty roots in the less predictable component of uncertainty - e.g. macro conditions - we rank the firms based on their proportion of ALU as a share of OU (the green line in Figure 8). The figure also shows the ratios for the sum of aggregate and sectoral uncertainty and the sum of all three tiers as a proportion of OU, which is the horizontal line equal to 1 by definition. In the figure, the distance between the blue and red lines represents the proportion of FLU out of OU.

We see that most of the uncertainty firms face stems from macro sources, which are more difficult to count as predictable components of volatility to firms. Furthermore, the nature of our sample - containing primarily larger firms in the economy - implies that this group of firms must have done better in resolving their internal issues. However, there is considerable heterogeneity among firms' experience of uncertainty.

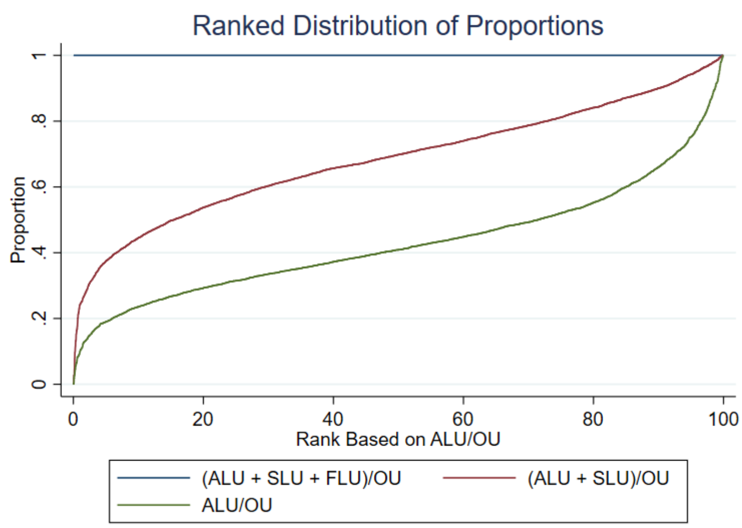


Figure 8: The Ranked Distribution of Firms' Proportion of Macroeconomic Uncertainty from their Overall Uncertainty

We can see that from around 30$^{\text{th}}$ percentile based on ALU/OU, around 60% of the uncertainty stems from macro (aggregate and sectoral) sources. As the smoothness in Figure 8 suggests, firms are strongly heterogeneous with respect to the proportionality and the nature of the uncertainty they face.

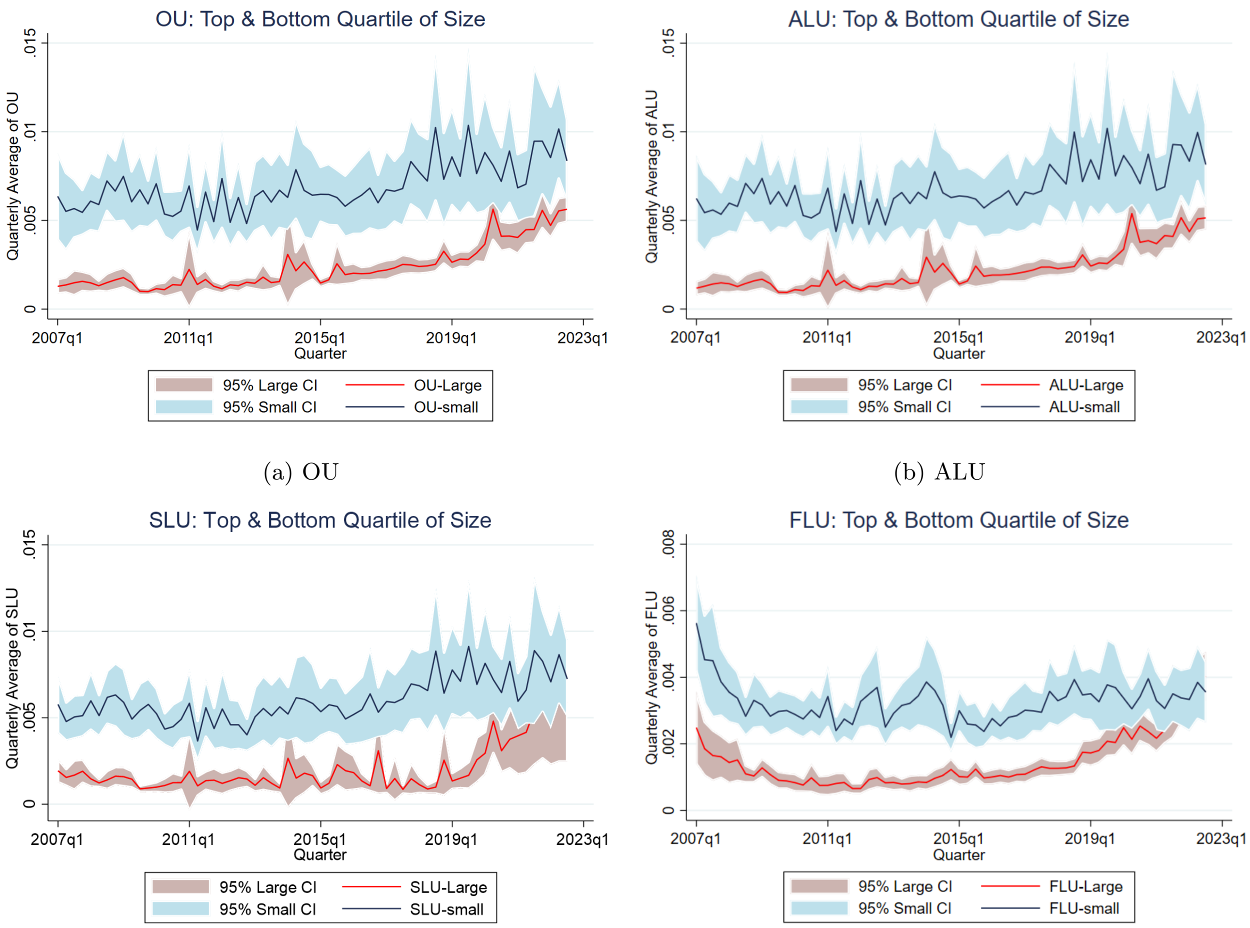
6.2 The role of size and age in explaining uncertainty heterogeneity

Firms face different levels of uncertainty based on their size (Ballantine, Cleveland and Koeller, 1993) and their age and experience (Drnevich and West, 2021). Business cycles affect young and small firms by a large amount (Clymo and Rozsypal, 2022). We regroup firms based on their presence in the groups of small (young) and large (old) firms based on the percentile of total assets (age) in each quarter (see the details in Section 3). This allows us to capture the firm dynamics better as firms grow and get small, enter or leave the markets. Such dynamics affect uncertainty in all of its components.[14]

6.2.1 Size and uncertainty heterogeneity

To study the size heterogeneity, we average the overall, firm, sectoral and aggregate uncertainties within each firm size group at each quarter in our sample. Figure 9 shows that the average overall uncertainty is much lower for large firms with respect to their smaller counterparts. The difference remained strong for both classifications and during the recessionary and non-recessionary periods.

[14] We also provide the results for very large (very old) and very small (very young) firms in the Appendix A.2 - where we show that the choice of quantile does not contradict our main takeaways.



(a) OU

(b) ALU

(c) SLU

(d) FLU

Figure 9: Uncertainty measures for different size groups based on total assets: large(top quartile) and small (bottom quartile) firms

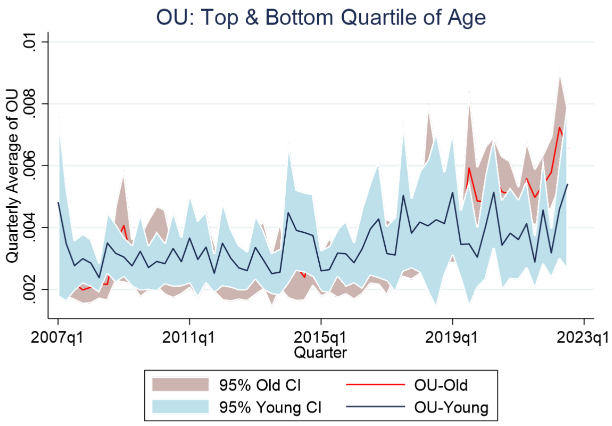
The results presented above are in line with Dunne, Roberts and Samuelson (1989) for the manufacturing sector: firms' size is an important determinant of growth at the firm level. With small firms facing more uncertainty, there is less chance for growth. The figure also shows that this also holds for the components of uncertainty, with a slight difference that there seems to be a catch-up pattern among firms in their SLU and FLU after the COVID outbreak.

We also present the standardised values of uncertainty. In essence, we standardise the time series at each firm to have a $\sim (0, 1)$ distribution. This approach can study how heterogeneity with respect to the business cycle exists and it can affect firms heterogeneously. We then average these values at each tier of uncertainty at each quarter. This technique provides us with a better tool to analyse our uncertainty tiers at different times. In Figure 18 in Appendix A.2, we can see that the large firms experienced more turbulence in both the Great Recession and COVID outbreak relative to their usual business, reflected strongly in sectoral and firm-level uncertainties. In contrast, smaller firms' uncertainty fluctuated more strongly in calmer periods. Ultimately, the larger firms have been experiencing extreme uncertainties after 2020, reaching a new peak every few quarters.

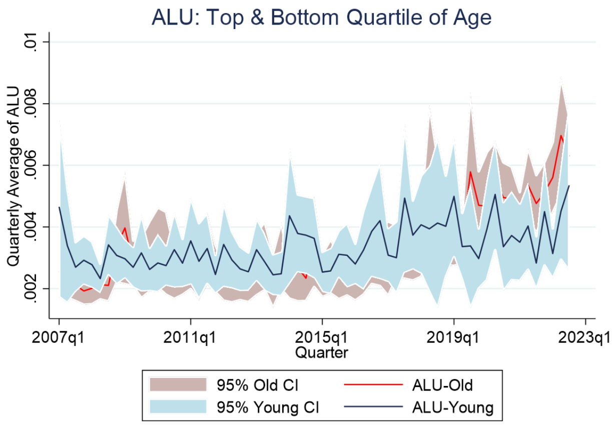
So far, we discussed how the level of uncertainty in all components is higher among smaller firms. Our follow-up analysis concerns the decomposition of uncertainty in each group. Put simply, we study the proportions of each component in each group at each point in time. The results of these proportions are provided in Figure 20 in Appendix A.2. While for both groups of small and large firms, the aggregate uncertainty constitutes a large proportion of uncertainty, the extent is larger among larger firms. This is intuitive since larger firms seem to have resolved the microeconomic conditions within their company - as well as their potentially higher market concentration in the sector which lowers their degrees of firm and sectoral uncertainty.

6.2.2 Age and uncertainty heterogeneity

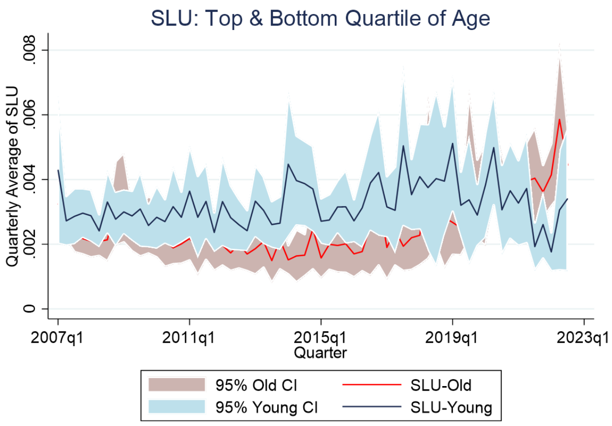
We continue with a study of the role that a firm's age plays in determining its uncertainty. As displayed in Figure 10, we find no significant evidence of difference among these groups in their volatility (Overall Uncertainty) or its components. However, older firms seem to be on the rise in their firm-specific uncertainty component, while on average, the sectoral uncertainty was experienced more among younger firms.



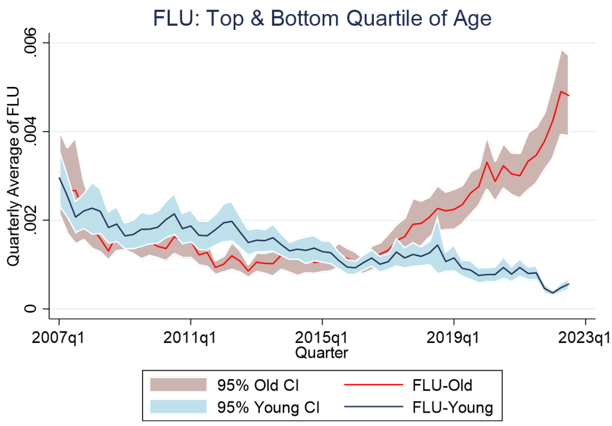
(a) OU



(b) ALU



(c) SLU



(d) FLU

Figure 10: Old and young firms' uncertainty components over time.

Similar to size, we average the standardised uncertainty for comparison over time among different age groups, presented in Figure 19. We can see that the aggregate component of older firms has increased over time, and sectoral and firm-level components have soared during the recessions, whereas younger firms' uncertainty is higher during the calmer episodes.

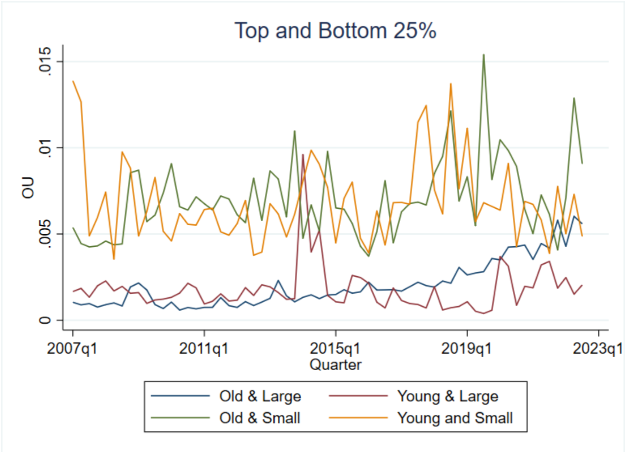
Some notes of caution: in our sample, young means "recently listed", not recently established. At each point, one may expect recently established firms to have more uncertainty. We do not have access to the establishment date of the entities in our sample and limit our attention to the concept of IPO's impact on firms. Once a firm is successfully IPOed, it receives large liquidity as well as an increase in reputation, sales and investments. This could cause a short-term moderating impact on uncertainty as it provides a buffer against idiosyncratic, aggregate and sectoral shocks. To find out if younger listed firms do not necessarily have lower uncertainty, we follow an alternative approach to classify our [listed] firms as old and young. We use the benchmark of older than 15 and younger than 5, as also similarly used by Ferrando et al. (2020). Any firm in between is classified as mature. 29% of the firms will be tagged as young, 27% will be known as old and 44% of the firms will be mature. The graphs of this analysis, provided in Appendix A.2 are found to be very similar to our analysis above, indicating no significant difference in levels of uncertainty among age groups.

Next, we ask the question of whether the proportions of types of uncertainty among young and old firms differ. We find substantially different patterns based on age (See Figure 21 in Appendix A.2). For the young firms and until 2020, all three components of uncertainty remained roughly in the region of 0.3-0.4. Since the COVID outbreak, however, the aggregate uncertainty proportion has increased sharply. Furthermore, we observe a substantial decrease in the firm-level component. Among larger firms, however, there has been a constant increase in the aggregate component until 2020. Amid the supply-chain-related shocks of COVID-19 in 2020, the large firms' sectoral uncertainty (as a proportion) has been on a negative-trend path over time.

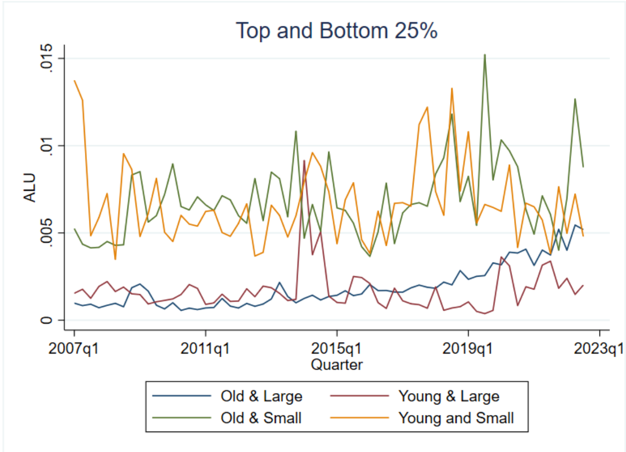
6.2.3 The interaction between size and age

Lastly, our analysis raises the question of whether the size of the recently-listed firm matters. To do so, we analyse our framework by dividing our sample into subsamples that interact with age and size.

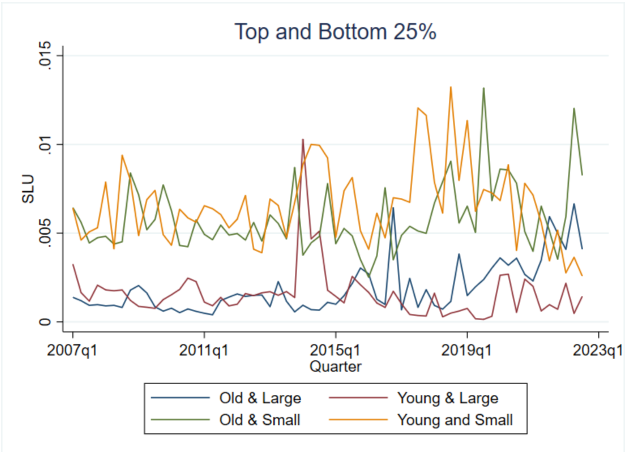
While the literature on firm growth has converged toward the finding that size and age have substantially different implications for firm growth (such as in Clymo and Rozsypal (2022)) - we can also question whether large firms are more likely to be old. Accumulating assets and employees takes time. Yet, with the convention of dividing firms into quartiles, we find that our sample includes a considerable number of large but young companies (3.2%, as opposed to 7.6% of large-old firms). A large and young firm might be exposed to higher volatility as it faces high financial uncertainty, for example, due to its unknown performance after the IPO date (Brown and Wiles, 2015) and lack of information on past performances. However, our findings reject such a link in almost all the components of uncertainty.



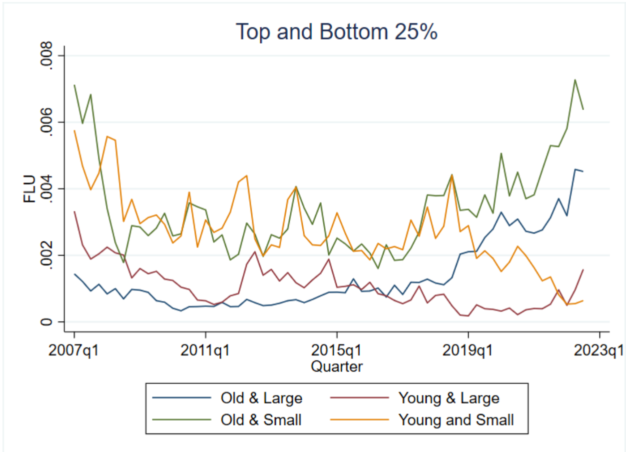
(a) OU



(b) ALU



(c) SLU



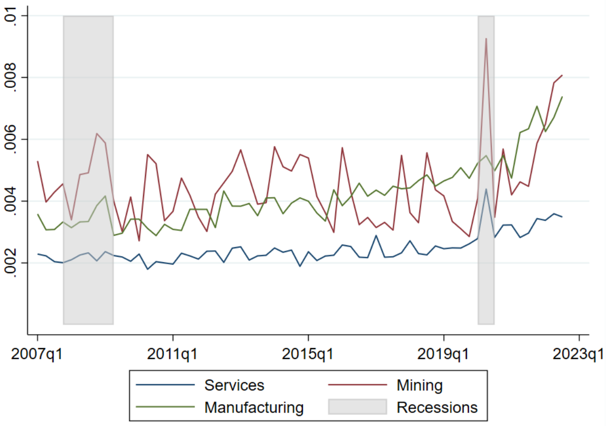
(d) FLU

Figure 11: Tiers of Uncertainty for the Interaction of Age and Size

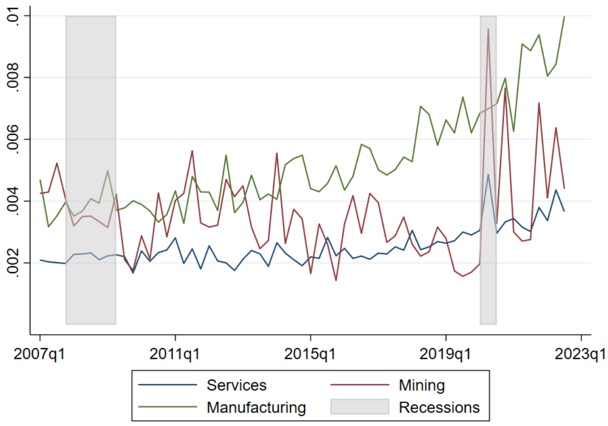
The firms' size drives the heterogeneity across most of our sample in different uncertainty components. The striking negative trend in the aggregate uncertainty for younger firms might have policy implications: the newer firms seem to be richer in information - through their data accumulation. This sort of entry with high information can reduce the uncertainty for a firm, for interchangeably important demand and production sources of uncertainty (Eeckhout and Veldkamp, 2022).

6.3 Heterogeneity of uncertainty across sectors

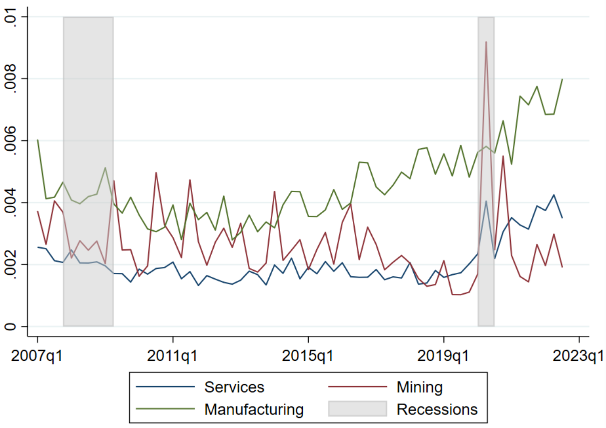
In this section, we study the characteristics of uncertainty across large sectors. First, we consider their evolution over time in Figure 12; we average SLU and ALU for each of these groups and find that they evolve as follows.



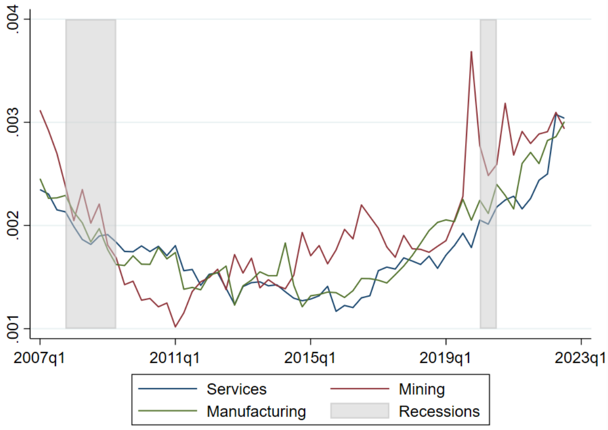
(a) OU



(b) ALU



(c) SLU



(d) FLU

Figure 12: Averaged aggregate and sector level uncertainties across large sectors

The moderate levels of uncertainty in the service sector, even in the recessions of 2008 and 2020, might be captured by the idea that their activities might be less dependent on the global supply chains. The very sharp peak of mining uncertainty during the 2020 supply chain crisis also stands out, while the positive trend of uncertainty in the manufacturing sector reflects the difficulties of this sector in conducting business in recent decades. Generally, our results confirm an aspect of the "decline in the U.S. manufacturing sector" as pointed out in detail by Charles, Hurst and Schwartz (2019): the manufacturing sector has experienced a drop in the hours worked in the last decades, as well as a sharp increase in capital intensity and stagnated output levels.

Ultimately, we suspect that the rise in manufacturing uncertainty can be related to supply chain disruptions. Intuition from Parast and Subramanian (2021) indicates that input supply disruptions can significantly affect firm performance and increase uncertainty in manufacturing firms through production bottlenecks. We obtain the series of the U.S. ISM manufacturing Supplier Deliveries Index from YCharts, and find a 68% correlation between the supplier deliveries index and uncertainty. Figure 25 in Appendix A.2 demonstrates how closely manufacturing uncertainty and supply delivery index are correlated.

7 Robustness Checks

Our novel strategy for decomposing uncertainty into different components should be robust to alternative specifications. An uncertainty decomposition exercise should perform well in identifying the idiosyncratic component - in our case, the firm-level uncertainty, as well as a fairly uncorrelated pair of macroeconomic components, namely sectoral and aggregate levels. Our measure can identify a firm-level uncertainty measure that is correlated with an extent of only 20% with respect to aggregate and sectoral levels. In this section, we check the robustness of our strategy through multiple specifications that have the potential to perform better than our model. Our methodology is robust to these specifications and can decompose uncertainty into desired tiers appropriately.

To fully ensure that our powerhouse is effective in disentangling the different components of overall uncertainty, we add the firm-level uncertainty measured in the first step of our analysis as a control in estimating the sector-level uncertainty in the second step. The regression results are in Table C.1 in Appendix C. Our baseline measure is robust to this specification: the resulted SLU and ALU are 99% correlated to their counterparts from the baseline specification. Appendix A.3 provides the scatter plots and related graphs.

One may argue that our approach divides the sample into too small subsamples in creating the common factor among firms in each industry. To demonstrate that our specification is robust to such claims, we divide the sample into 1-digit NAICS sectors, which divides our sample into nine groups. We then include the new common factor in our estimation of SLU and show that the resulting SLU is almost 98% correlated to the baseline SLU, and the ALU is at the 90% correlation level with the baseline ALU.

Ultimately, we suspect whether the seasonality issue might arise in our estimations. To test our methodology against this argument, we perform an identical analysis with respect to our baseline estimations but with four lags in sales instead of only one. We find a range of [0.75-0.86] pairwise correlation between the new values for each tier and the baseline specification values. However, this new specification correlates less strongly with other economic uncertainty indices.[15]

8 Conclusion

We introduce a novel uncertainty measure computed using firms' balance sheet data that generates three different tiers of uncertainty from firms' overall uncertainty. We show that our uncertainty index driven from micro-data correlates with those driven from aggregated data like macro variable dispersion or media discussion on uncertainty. Our measure of aggregate uncertainty also peaks around recessions and economic and political turbulence. We also show the presence of substantial heterogeneity among firms and sectors: large firms experience much lower uncertainty than small firms. Higher uncertainty for smaller firms means lower growth of these firms over time as they might become more and more cautious and delay their investments and hiring decisions. This is a new channel through which uncertainty potentially dampens sectoral and aggregate growth. Furthermore, we show that manufacturing has exhibited higher levels of uncertainty across our sample, except for the COVID shock primarily represented in the mining sector - an interesting puzzle for future research to disentangle the COVID shock across sectors more formally. The services sector experienced substantially less uncertainty over time - justifying the higher rate of firms entering this sector during the last decades. All in all, our approach fills the gap regarding uncertainty heterogeneity in the literature. It provides evidence for the former and sheds light on the similarity between identified aggregate uncertainty from microdata and uncertainty measured using aggregated data.

[15] Interestingly, the inclusion of 4 lags de-trends the quarterly average of ALU over time and increases the role of recessions. Furthermore, we can see a drop in the persistence of uncertainty after COVID-19 - as annual changes were non-responding to the short-term events.(see Figure 29 in Appendix A.3).

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A Graphs

A.1 Descriptive Graphs and General Attributes

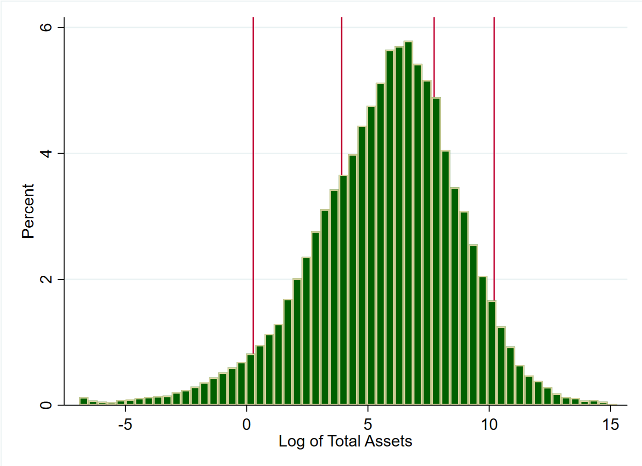


Figure 13: The Distribution of Total Assets and 10th, 25th,75th and 90th Percentiles.

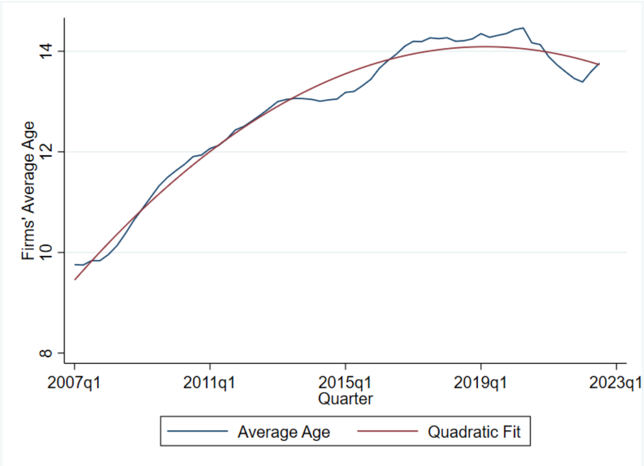
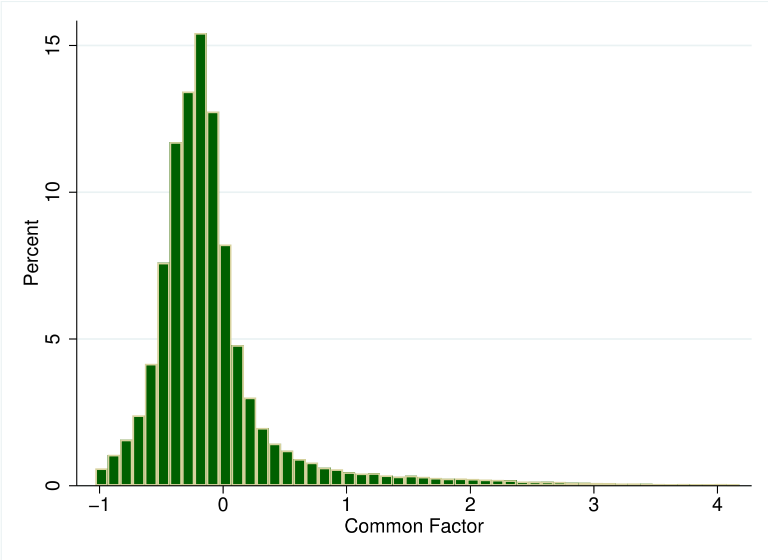
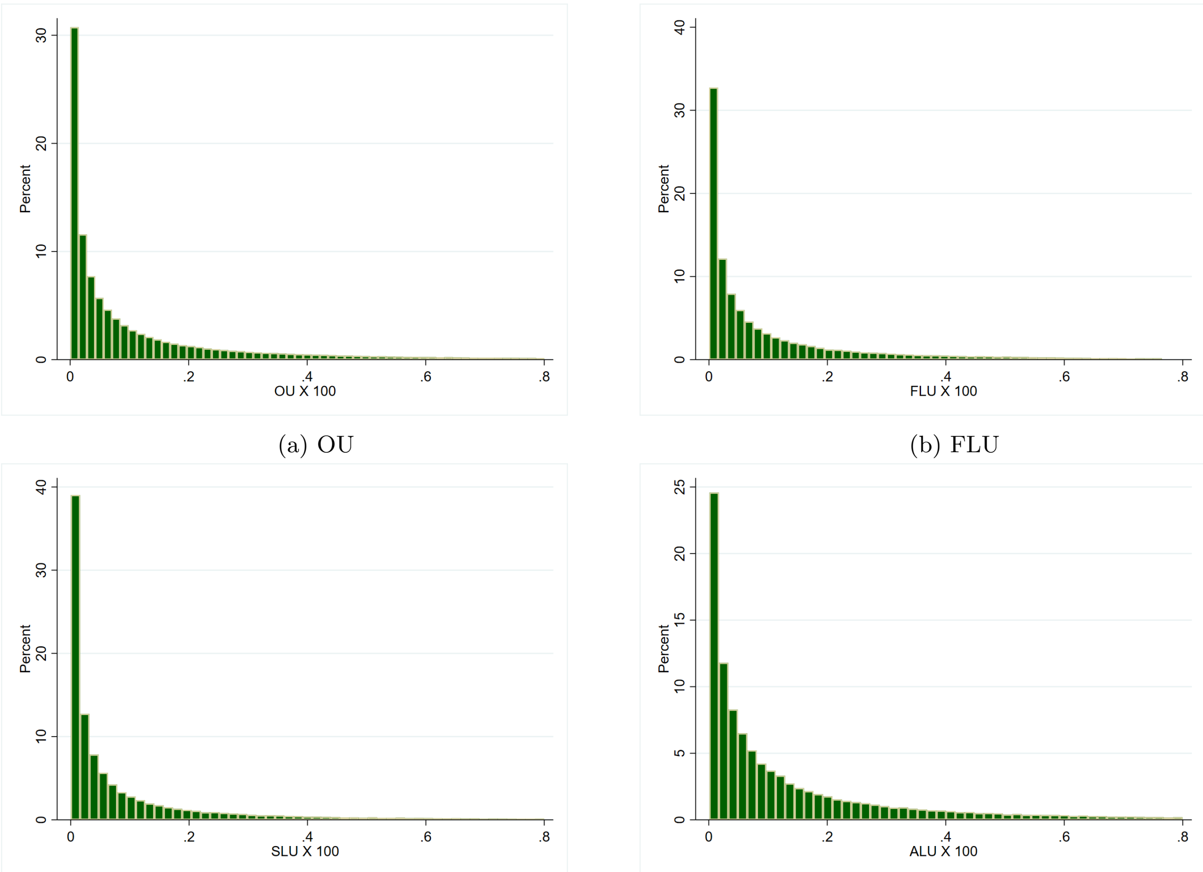


Figure 14: The ageing of the firms in our sample over time vs a quadratic fit.

Figure 15: The Distribution of the Common Factor.



(from the 5th to 95th percentiles) to disregard potential outliers.



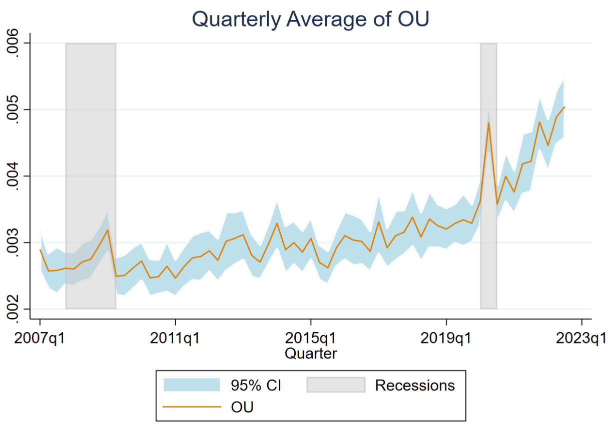
(a) OU

(b) FLU

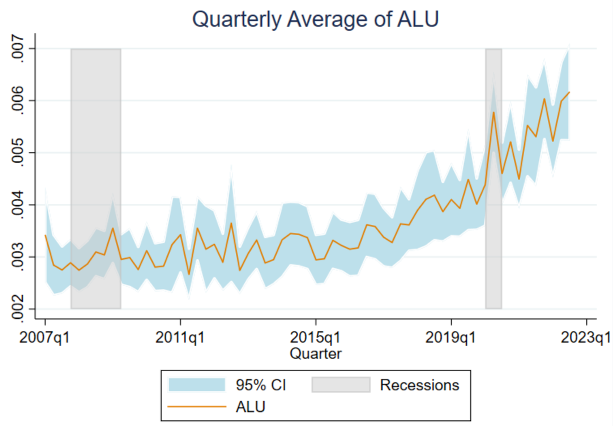
(c) SLU

(d) ALU

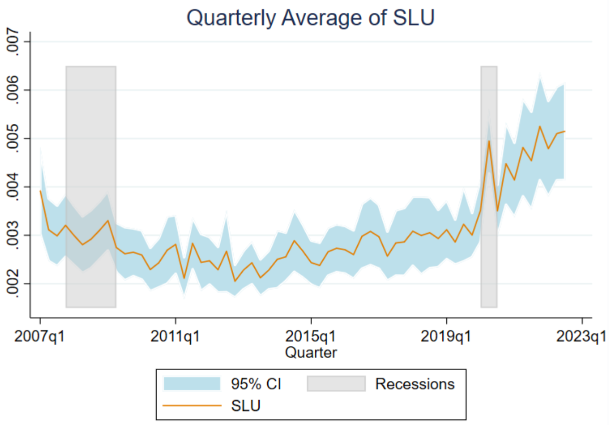
Figure 16: The Distribution of Uncertainty Components.



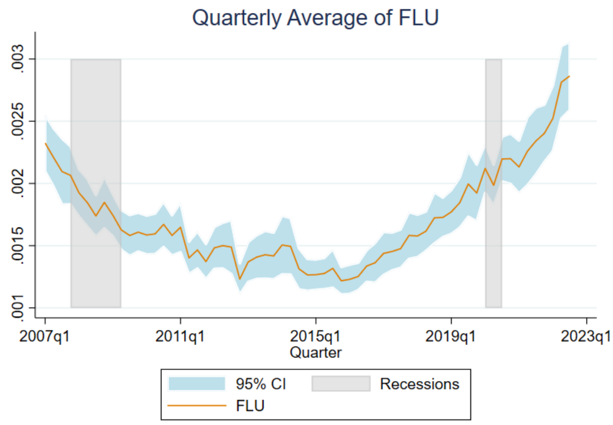
(a) OVerall Uncertainty (OU)



(b) Aggregate Level Uncertainty (ALU)



(c) Sector Level Uncertainty (SLU)

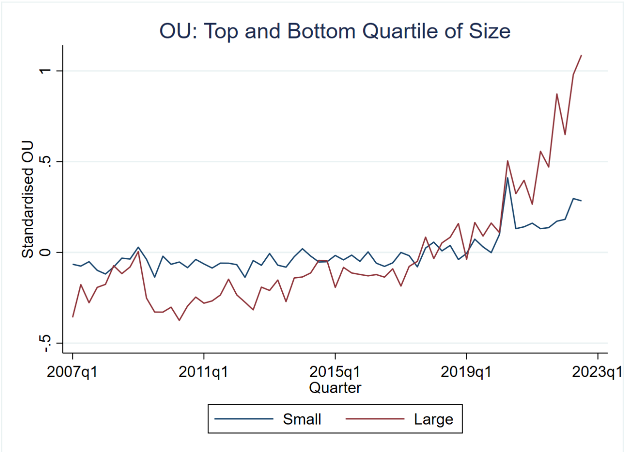


(d) Firm Level Uncertainty (FLU)

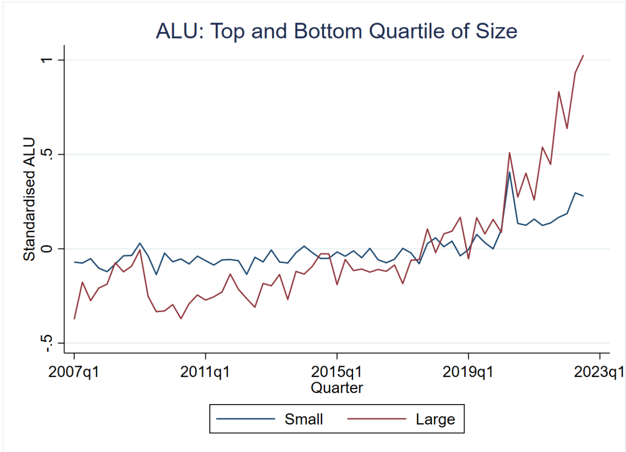
Figure 17: U.S. Uncertainty Components between 2007 and 2022 vs Recessions.

A.2 Heterogeneity Graphs

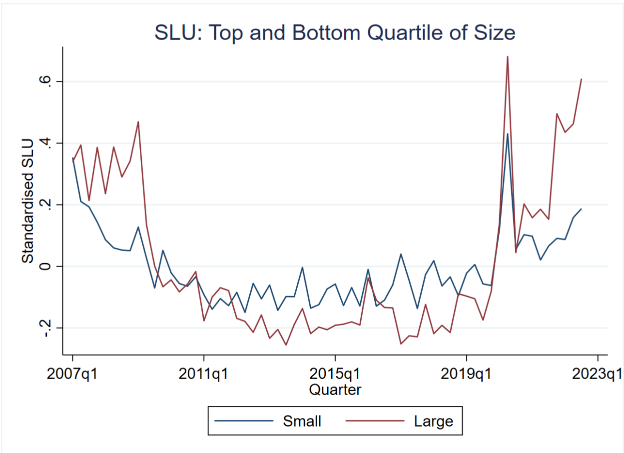
Large vs Small, Old vs Young - Standardised



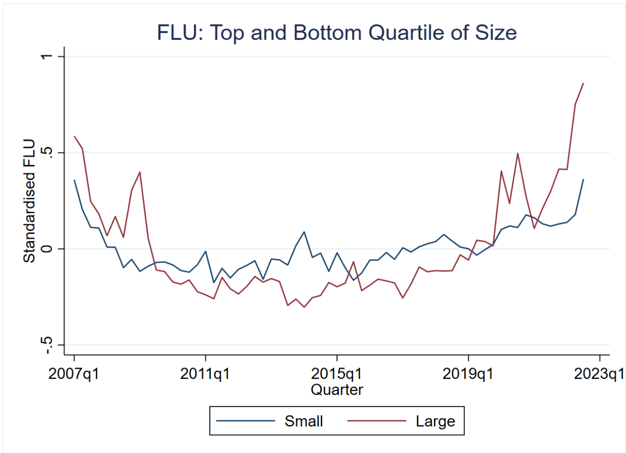
(a) OU



(b) ALU

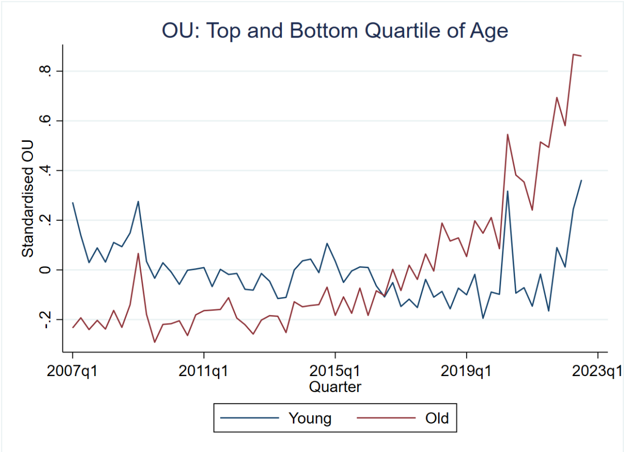


(c) SLU

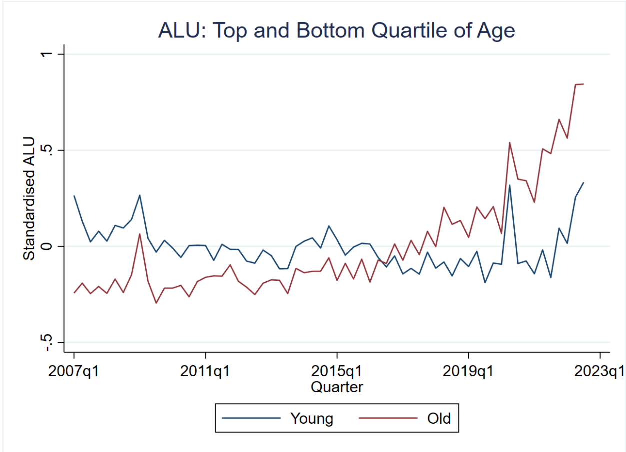


(d) FLU

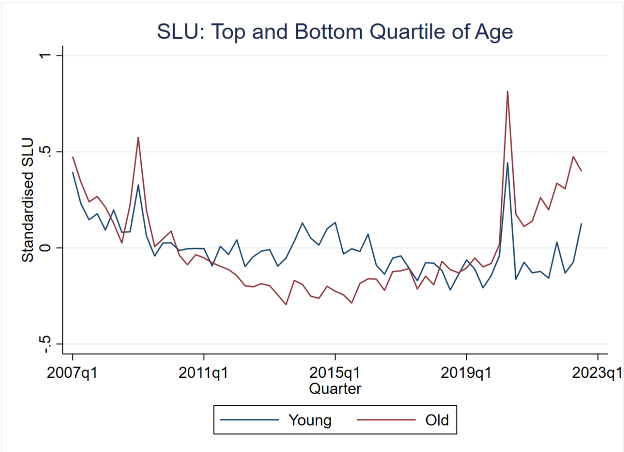
Figure 18: Large (top quartile) and small (bottom quartile) firms' standardised uncertainty measures over time.



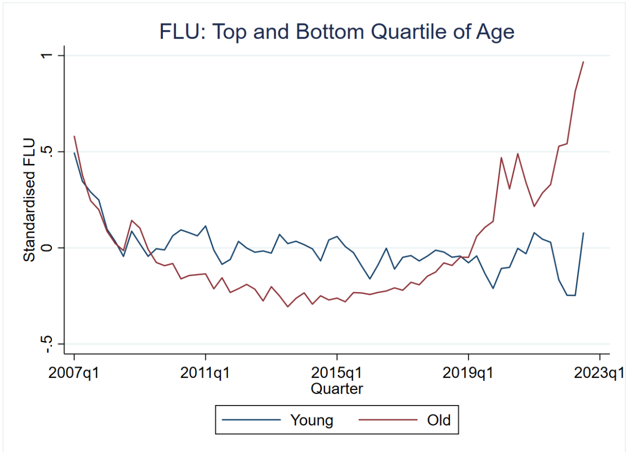
(a) OU



(b) ALU



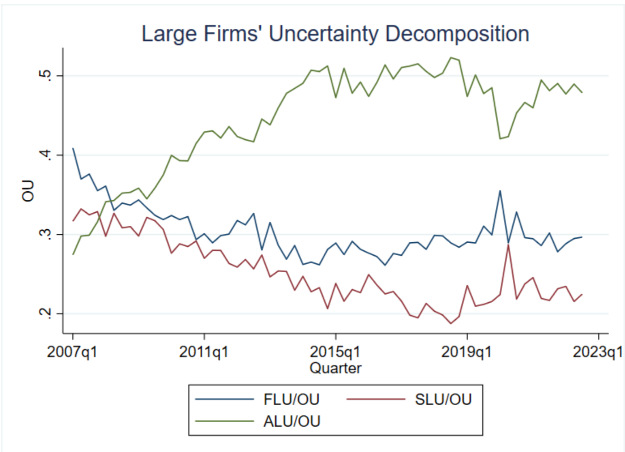
(c) SLU



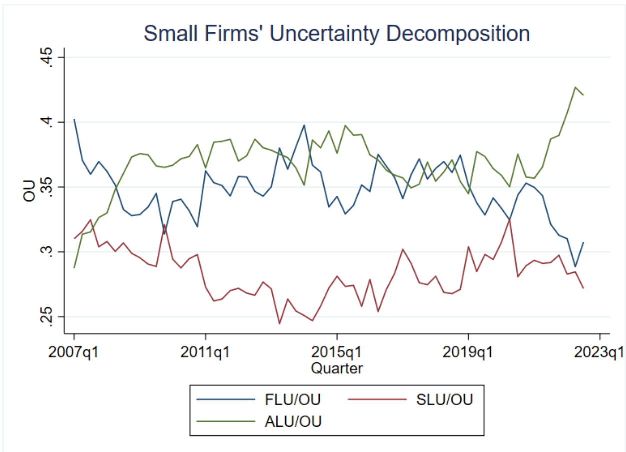
(d) FLU

Figure 19: Old (top quartile) and Young (bottom quartile) firms' standardised uncertainty measures over time.

Large vs Small, Old vs Young - Decomposition

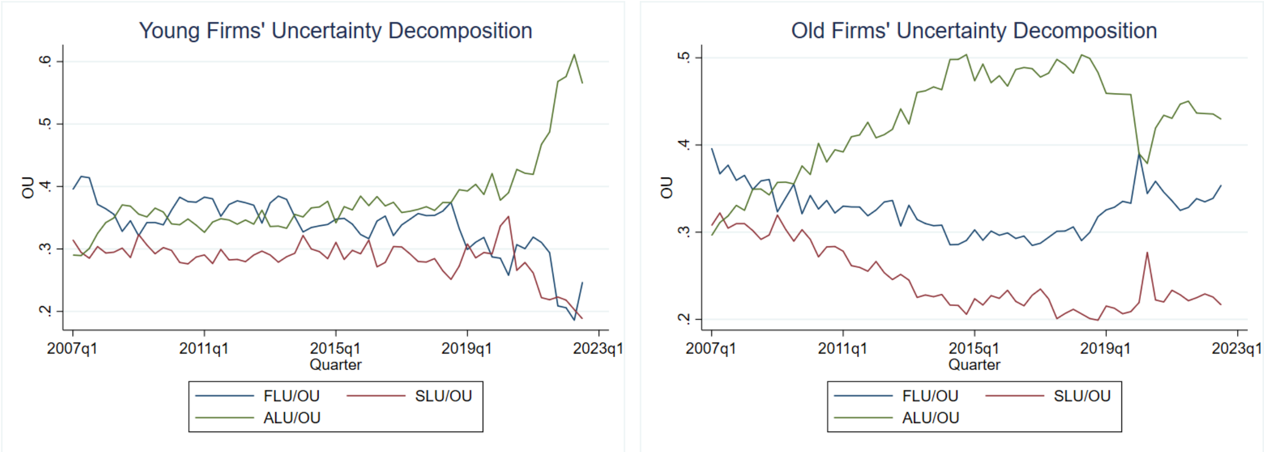


(a) ALU



(b) SLU

Figure 20: Large and Small Firms' Proportions of Uncertainty Tiers Over Time

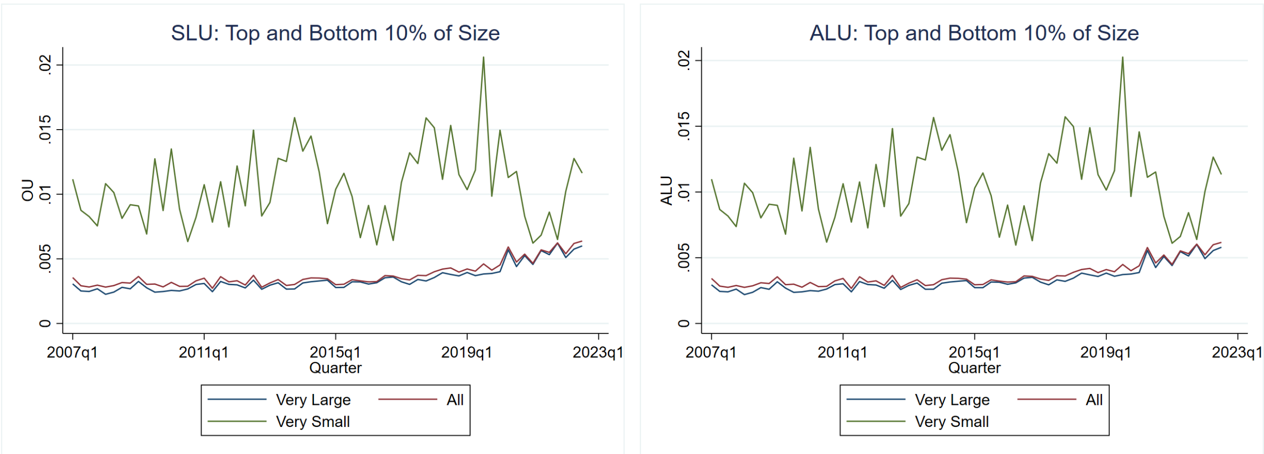


(a) ALU (b) SLU

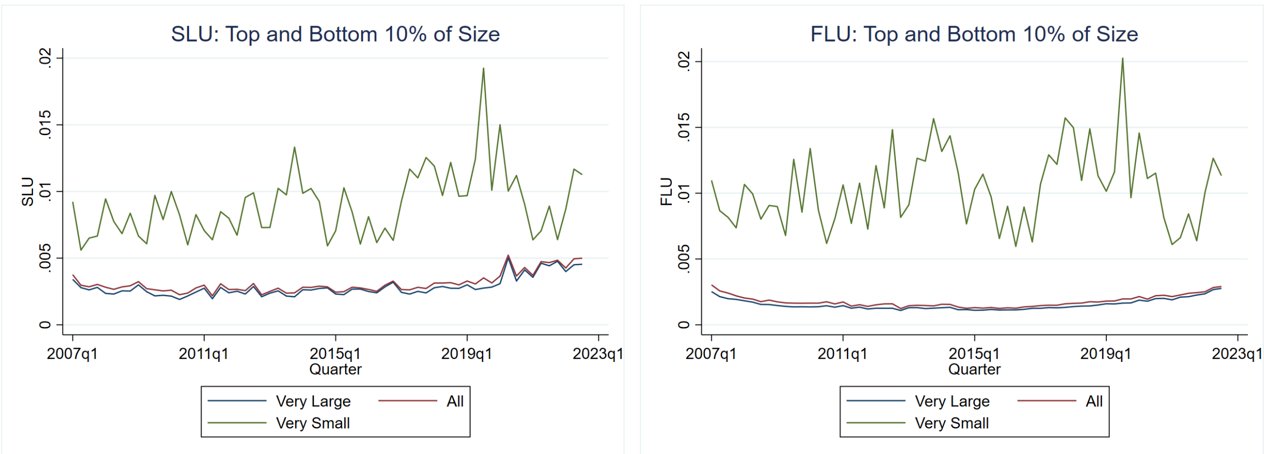
Figure 21: Old and young firms' proportions of uncertainty tiers over time.

Heterogeneity Using Smaller Groups

Very Large Firms vs Very Small Firms



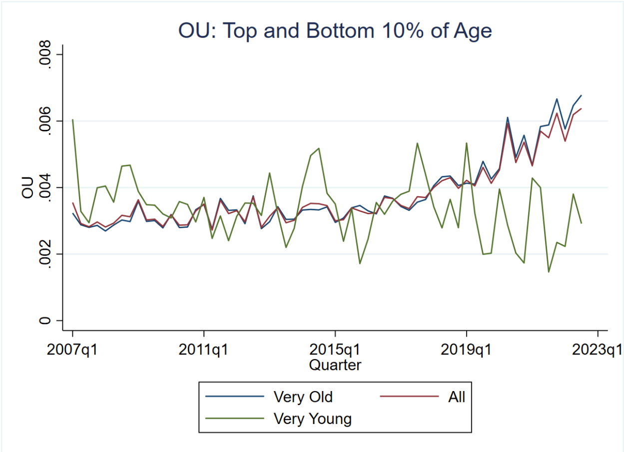
(a) OU (b) ALU



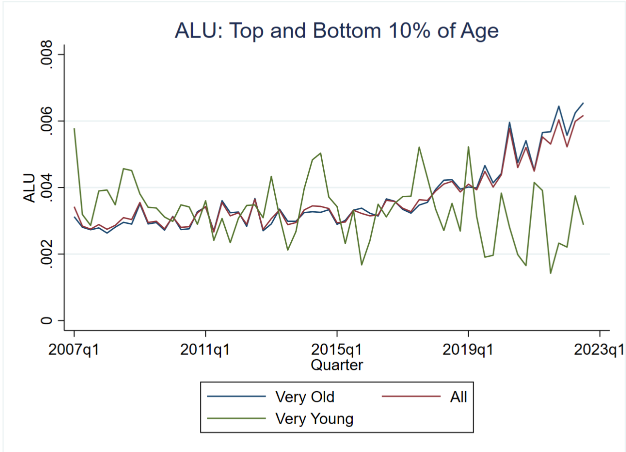
(c) SLU (d) FLU

Figure 22: Very Large and Very Small Firms' Uncertainty Tiers Over Time

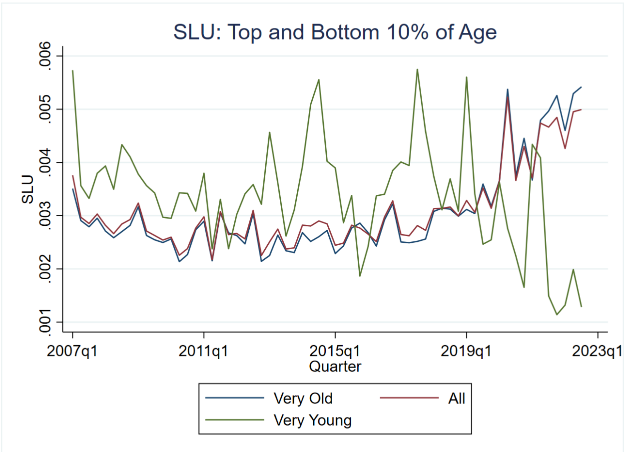
Very Old Firms vs Very Young Firms



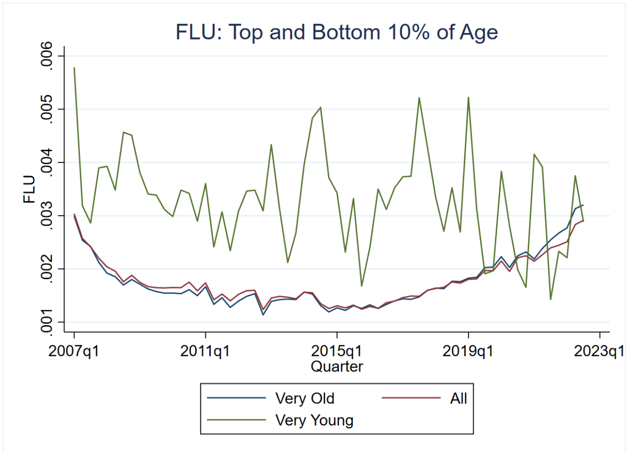
(a) OU



(b) ALU



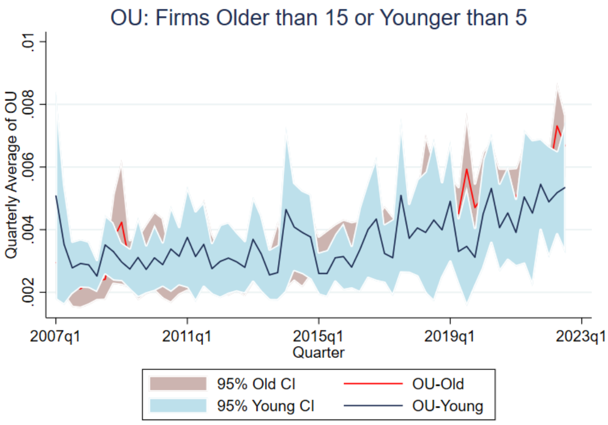
(c) SLU



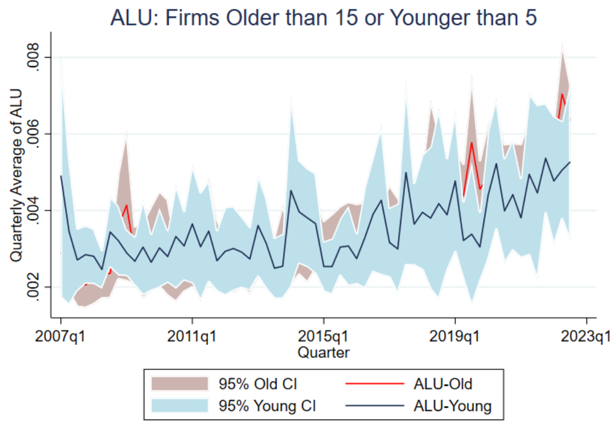
(d) FLU

Figure 23: Very Old and Very Young Firms' Uncertainty Tiers Over Time

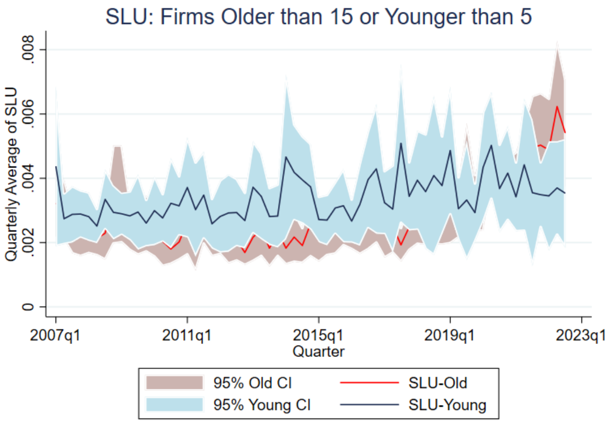
Alternative Classification for Age



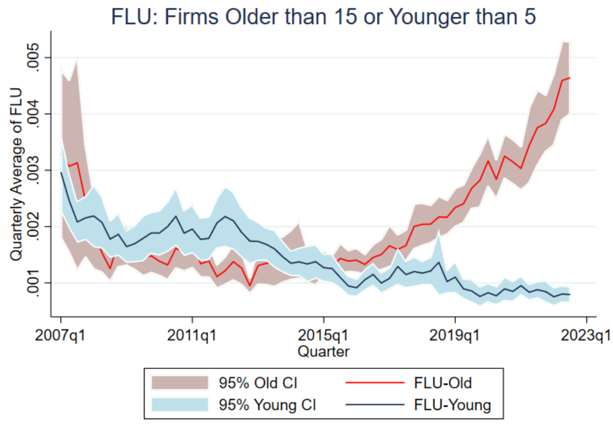
(a) OU



(b) ALU



(c) SLU



(d) FLU

Figure 24: Old and Young Firms' Uncertainty Tiers Over Time - Alternative Specifications

Sectoral Heterogeneity

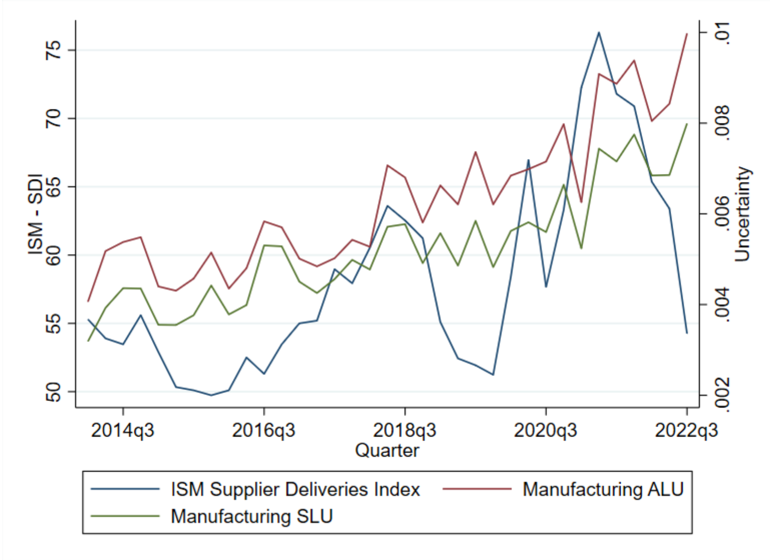
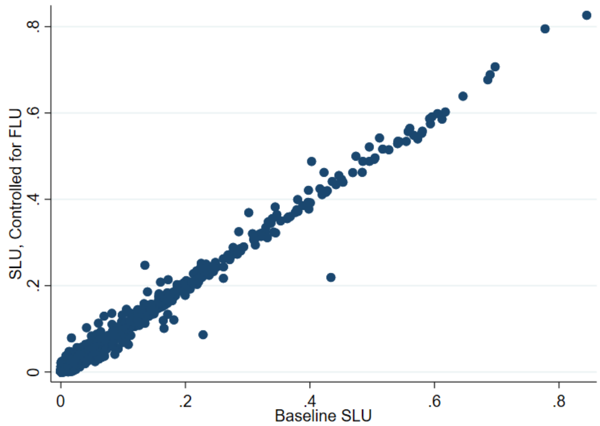
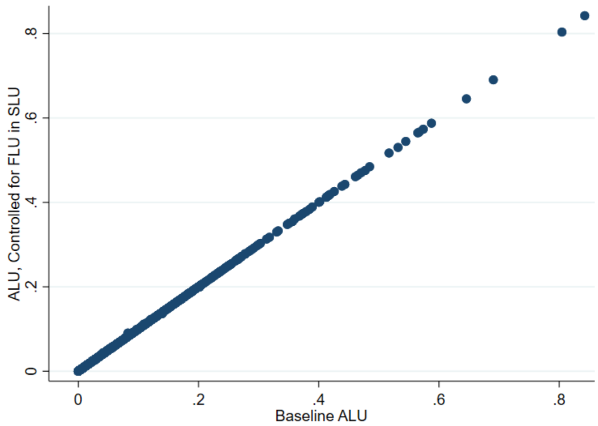


Figure 25: Manufacturing uncertainty and the Supply Delivery Index.

A.3 Robustness Checks

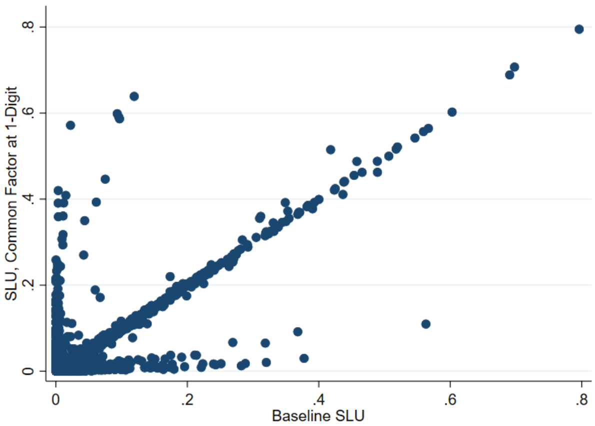


(a) SLU vs SLU Controlled for FLU

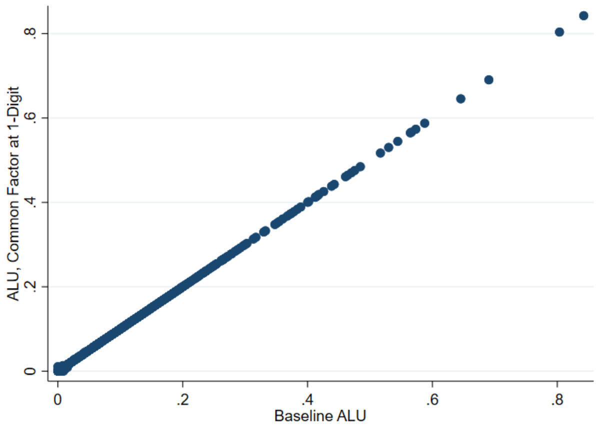


(b) ALU vs ALU Controlled for FLU

Figure 26: The scatter plot for ALU and SLU between the baseline specification and the alternative specification #1

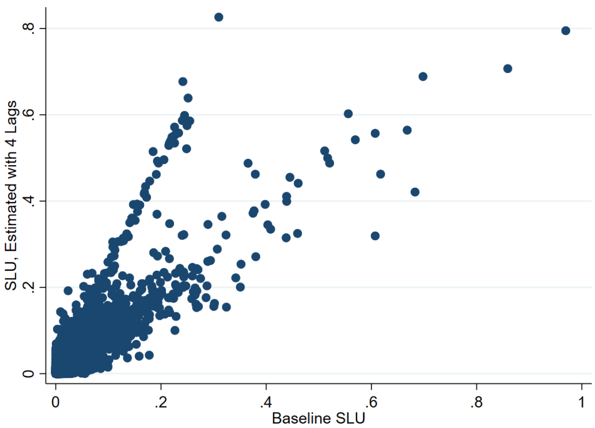


(a) SLU vs SLU with 1-Digit CF

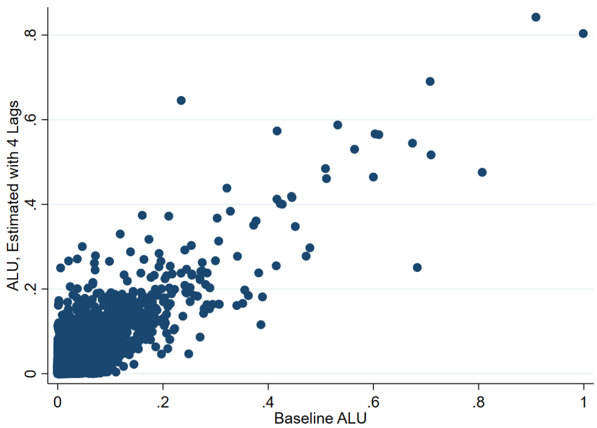


(b) ALU vs ALU with 1-Digit CF

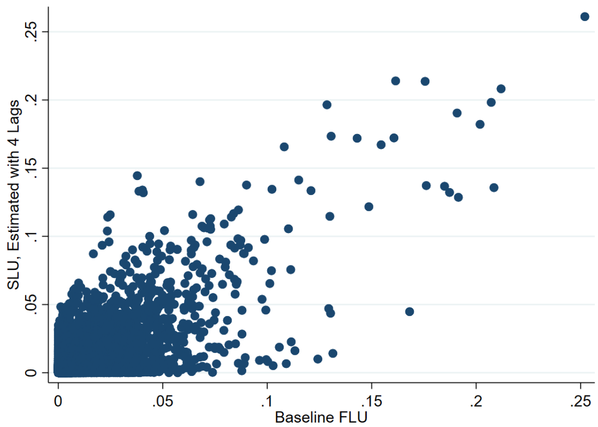
Figure 27: The scatter plot for ALU and SLU between the baseline specification and the alternative specification #2



(a) SLU vs SLU with 4 Lags



(b) ALU vs ALU with 4 Lags



(c) ALU vs ALU with 4 Lags

Figure 28: The scatter plot for ALU and SLU between the baseline specification and the alternative specification #3 - Disregarding the negative values

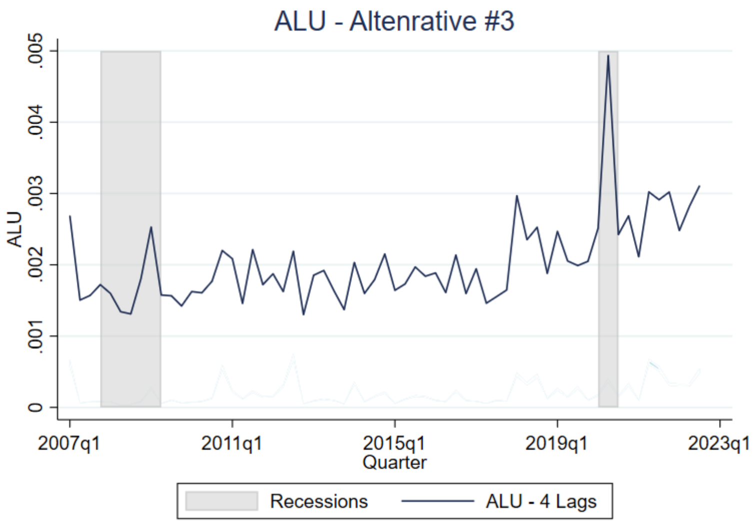


Figure 29: ALU - alternative specification #3

B Descriptive Statistics

The Sample including Canadian firms:

Variable	Content	Observations	Mean	SE	Range
S	Net Sales	718,548	3.71	2.87	-6.91 - 12.24
CF	Cash Flow	460,711	2.82	3.07	-6.91 - 12.57
TA	Total Assets	791,473	5.42	3.10	-6.91 - 15.27
MV	Market Value	481,640	5.32	2.61	-9.21 - 14.89
LT	Total Liabilities	792,417	4.67	3.26	-6.91 - 15.26
INT	Intangible Assets	444,227	3.81	3.08	-6.91 - 12.6
TR	Total Revenue	655,227	3.74	2.94	-6.91 - 12.24
Computed Variables					
Age	Quarter - IPO	384,140	1.98	1.1	-5.90 - 4.30
Capital Intensity	TA / TR	631,138	2.01	1.32	-12.71 - 14.72
Int/TA	Int/Total Assets	716,958	0.12	0.20	-0.05 - 2.89

Table B.1: Firm-Level Variables Descriptive Statistics

Source: Compustat database in Quarterly frequency for 2000Q1-2022Q4. Geographical coverage includes firms registered in the United States and Canada and filed in the Compustat database.

C Regressions of Uncertainty Derivation

GMM Estimators for the baseline specification :

	Dependent Variable: Log of Sales$_{i,t}$		
Uncertainty Component →	(OU)	(FLU)	(SLU)
Log of Sales$_{i,t-1}$	0.3825***	0.6223***	0.3791***
	(0.0017)	(.001264)	(0.0030)
Log of Age$_{i,t}$	-	0.0249***	-
	-	(.0013)	-
Log of Market Value$_{i,t}$	-	0.2423***	-
	-	(.0012)	-
Log of Capital Intensity$_{i,t}$	-	-0.4727***	-
	-	(.0015)	-
$Cfact_{i,t}$	-	-	0.6486***
	-	-	(0.0086)
Firm FE	✓	✓	✓
Time FE	✓	✓	✓
Observations	679,977	166,023	163,498
Firms	19,896	5,695	5,830
Wald χ^2	49007.19, P=0	1.36e+06, P=0	1.36e+06, P=0

*** Significant with 99% Confidence Interval, ** Significant with 95% Confidence Interval, * Significant with 90% Confidence Interval

The Regression Results for Robustness Checks

Table C.1: Regression Results for SLU with Controlling for FLU

	Dependent Variable: Log of Sales$_{i,t}$
Log of Sales$_{i,t-1}$	0.3475***
	(0.0033)
$CFact_{i,t}$	0.6600***
	(0.0104)
$FLU_{i,t}$	-9.0410***
	(0.5230)
Firm FE	✓
Sector FE	✓
Observations	134,826
Firms	4,816
Wald χ^2	16597,68, P=0

*** Significant with 99% Confidence Interval, ** Significant with 95% Confidence Interval, * Significant with 90% Confidence Interval

D Results from a simple GLS

Table D.1: Regression Results for OU

	Dependent Variable: Log of Sales$_{i,t}$
Log of Sales$_{i,t-1}$	0.9113***
	(0.0005)
C	0.2972***
	(0.0025)
R-Squared	0.9714
Observations	590,893
Firms	17,081
Time FE	X
Sector FE	X
Wald χ^2	3.19e+06, P=0

***:$p < 0.01$, **:$p0.05$ & *: $p < 0.10$

Table D.2: Regression Results for FLU

	Dependent Variable: Log of Sales$_{i,t}$		
	(1)	(2)	(3)
Log of Sales$_{i,t-1}$	0.9108***	0.6223***	0.6058***
	(0.0005)	(.001264)	(.0013)
Log of Age$_{i,t}$	-	0.0249***	0.0232***
	-	(.0013)	(.0013)
Log of Market Value$_{i,t}$	-	0.2423***	0.2427***
	-	(.0012)	(.0012)
Log of Capital Intensity$_{i,t}$	-	-0.4727***	-0.4892***
	-	(.0015)	(.0015)
Intangible/Total Assets$_{i,t}$	-	-	0.4919***
	-	-	(.0080)
R-Squared	0.9709	0.9621	0.9608
Observations	590,893	166,023	165,768
Firms	17,081	5,695	5,693
RMSE	0.4499	0.3543	0.3491
Time FE	✓	✓	✓
Sector FE	✓	✓	✓
Wald χ^2	3.80e+06, P=0	1.36e+06, P=0	1.36e+06, P=0

***:$p < 0.01$, **:$p0.05$ & *: $p < 0.10$

Table D.3: GMM Estimators to Solve for Heteroscedasticity

	Dependent Variable: Log of Sales$_{i,t}$
Log of Sales$_{i,t-1}$	0.9132***
	(0.0010)
$CFact_{i,t}$	0.0673***
	(0.0023)
C	0.8890**
	(0.3275)
R-Squared	0.9643
Observations	149,726
Firms	5,352
Time FE	✓
Sector FE	X
Wald χ^2	9.13e+5., P=0

***:$p < 0.01$, **:$p0.05$ & *: $p < 0.10$

Table D.4: Regression Results for SLU