Explaining the Persistent Effect of Demand Uncertainty on Firm Growth

Gigout, Timothee and Bricongne, Jean-Charles

Collège de France, Banque de France

1 May 2019

Explaining the Persistent Effect of Demand Uncertainty on Firm Growth

Jean-Charles Bricongne * Timothee Gigout†

May 30, 2019

Abstract

We study the effect of demand uncertainty on firm growth. We use product-level bilateral trade data to build an exogenous firm-level measure of the uncertainty of demand shocks. We match it with exhaustive custom and fiscal data between 1996 and 2013. An increase in uncertainty has a negative and persistent impact on the growth of exposed firms. This suggests a different underlying mechanism from a simple real-option effect. Financially constrained firms experience a much sharper and longer slowdown. Sectoral comovement is also a key factor explaining the persistent effect of uncertainty.

JEL classification: F23, D81, D22, F61

Keywords: Uncertainty; demand shock; Firm-level; Dynamics; Heterogeneity.

Acknowledgement: We thank participants of the 18th Doctoral Meetings in International Trade and International Finance, the 2018 Meetings of the French Economic Association, the Banque de France PhD seminar and the 2018 CREA-IZA Workshop. In particular, we are grateful to Clement Malgouyres, Antonin Bergeaud, Simon Ray, Matthieu Lequien, Nicolas Coeurdacier, Jose De Sousa, Gonzague Vannoorenberghe, Matthieu Bussière, Michel Beine and Thierry Mayer.

*Banque de France - Commission Européenne - Sciences-Po Paris, LIEPP - Université de Tours, LEO, Email: jean-charles.bricongne@banque-france.fr.

†Collège de France - Université Lille I, Email: timothee.gigoutmagiorani@gmail.com.

1 Introduction

The increase in cross-border trade and financial linkages since the 1990's has led to a greater exposure of domestic agents to shocks abroad. More firms are now dependent on inherently uncertain demand conditions. In this paper, we investigate how the uncertainty around the realization of demand shocks affects the growth dynamic of French manufacturing firms between 1996 and 2013. We build a measure of demand uncertainty by computing the dispersion of estimated demand shocks from the highly dis-aggregated BACI bilateral trade database. We then document the effect of an increase in demand uncertainty on employment and investment growth using French fiscal data. A striking result is the persistent negative effect of a one-time uncertainty shock. The effect lasts for up to 5 years for both investment and employment. It is not followed by a period of compensation which makes those losses permanent. We find that losses are magnified for financially constrained firms and firms with high correlation to their industry.

The starting point of our paper is to compute a firm-level measure that captures the uncertainty of demand shocks. Some studies use aggregate measures of uncertainty (Baker et al. (2016), Julio and Yook (2012) or Bussiere et al. (2015))). Others use stock market based firm-level measures (Bloom et al. (2007), Barrero et al. (2017) or Hassan et al. (2017)). We choose instead to measure uncertainty using the firm exposure to the dispersion of estimated foreign demand shocks. It has three distinct advantages. First, it allows us to focus on one properly identified form of uncertainty, i.e. demand uncertainty. Second, it provides an exogenous firm-level measure that we can causally link to the firm outcomes. Lastly, we obtain a wider and more representative sample than one obtained using publicly listed firms.

To compute this measure, we follow a recent strand of literature relying on the computation of foreign demand shocks. See Esposito (2018) for a review. Using the highly disagregated database BACI (Gaulier and Zignago, 2010), we first estimate `product`×`exporting-country`×`importing-country`×`year` idiosyncratic demand shocks. We then aggregate those shocks by measuring their mean and dispersion at the `sector` × `importing-country` × `year` level. We use the dispersion as a proxy for uncertainty. Exports from France are excluded to prevent endogeneity in the variations of those measures. To illustrate, the country-sector with the highest demand uncertainty in our sample is the manufacture of coke and petroleum in Nigeria in 2010 which coincides with the death of the sitting president and the beginning of the first major terror attacks by Boko Harram. We typically observe the highest values for other emerging countries (Mali, Syria, Central African Republic) in raw material transformation sectors (manufacture of wood, manufacture of other transport equipment, manufacture of paper, etc.). Finally, to obtain a firm-level measure, we use a weighting scheme instrument as in Aghion et al. (2017) and Mayer et al. (2016). We exploit differences in the firms' initial exposures to the mean and dispersion of shocks associated with their own sector in any given importing country. The mean represents the firm specific foreign demand, whereas the dispersion represents the firm specific uncertainty of this demand.

We then regress several outcomes related to firm growth (Employment, investment, debt, etc.) on this measure of uncertainty. We use Local Projections methods (Jordà, 2005) to assess the persistence of the effect a one time change in uncertainty. Local Projections have recently been introduced for micro data where they provide a parsimonious and tractable alternative to VAR models to compute impulse response functions in the presence of potential non-linearities (see Favara and Imbs (2015), Crouzet et al. (2017) and Cezar et al. (2017)). We find that following a one standard deviation increase in uncertainty, firms lower their investment growth by -0.453 (s.e.= 0.114) percentage point and their employment growth by -0.581 (s.e.= 0.095) percentage point. The negative effect lasts for 5 years for both investment and employment. It does not exhibit any evidence of post-shock compensation (i.e. a positive value of the coefficient of uncertainty). Taken together, those results show that uncertainty has a permanent negative effect on firm growth. Our key result contrasts with a central prediction from the real-option theory. The value of the option of waiting should only temporally increase while there is uncertainty about future outcomes. In this model, firms should then postpone investment and compensate once the uncertainty is resolved (Bernanke, 1983). We show that some of the size and persistence of the effect we uncover can be explained by its interaction with financial frictions. However, even non financially constrained firms still experience a slight growth slowdown. The ability to reverse the decision to scale up by selling the newly acquired production capacity on a secondary is another candidate explanation. We also find that firms with low irreversability (measured by the correlation of the firm with the sales of its industry) do not suffer persistent effects from uncertainty. Whereas firms with high correlation experience a much longer downturn.

A tangential benefit of our approach of using foreign demand shocks is to allow us to measure the effect of the transmission of uncertainty abroad on the growth of domestic firms. Our study contributes to the debate of the effect of trade on firm dynamics. Many studies have now documented the importance of idiosyncratic demand shocks to aggregate fluctuations. Garin et al. (2017) investigate the impact of idiosyncratic foreign demand shocks on firm output and workers individual wages. di Giovanni et al. (2017) show how idiosyncratic shock drives aggregate fluctuations through large firms. Hummels et al. (2014) find that an exogeneous rise in foreign demand increases employment and wages for both skilled and non skilled workers. Other studies have focused on how idiosyncratic shock uncertainty affects exporters' behavior. It leads to lower than optimal size of supplier to allow for diversification (Gervais, 2018). Only large firms really benefit from diversification opportunities (Vannoorenberghe et al., 2016). While Esposito (2018) shows that risk diversification leads to wellfare gains. Vannoorenberghe (2012) shows that higher export share implies higher volatility of domestic sales. De Sousa et al. (2016) find that expenditure uncertainty reduces exports. Especially, more productive firms tend to abandon market shares in volatile destinations to less productive firms. Our study complements those results by showing that losses caused by a 2^{nd} moment shock (i.e. higher uncertainty) may potentially offset gains from a 1^{st} moment shock (i.e. higher demand). We show that the uncertainty of demand has long lasting consequence for the growth of manufacturing firms. The failure to take into account demand uncertainty could lead to overestimating gains from trade.

The reminder of the paper is organized as follows. Section 2 describes the data and our methodology to compute the uncertainty of idiosyncratic demand shocks. Section 3 provides our empirical results regarding the effect of uncertainty on firm growth. We show the robustness of our results in Section 4. Section 5 concludes.

2 Data

In the following subsections, we describe our data sources as well as the construction of our variables of interest. We then provide some stylized facts concerning our new variables.

2.1 Data Sources

We build a database of matching fiscal, export and employment benefit data of French firms between 1995 and 2013. We use export data from the French customs database to compute firm-level exposure to foreign demand shocks and uncertainty. Firm accounting data come from the French fiscal database FARE and FICUS. We use it to compute most of our control (eg. productivity, cash flow, etc.) and dependent variables (investment, employment). It also provides us with the firm primary sector of activity. Employee level data comes from the annual social data declaration DADS. It allows us to decompose how firms arbitrage between workforce size, structure and wages. It contains one observation per work contract with information regarding the type of contract and various employee (age, gender, etc.) plus firm characteristics (size, county, etc.). We calculate individual hourly wage growth rates then we average them at the firm level. We use LIFI to control whether the firm belongs to a group. We use BACI (Gaulier and Zignago, 2010) to compute import demand moments, including our uncertainty proxy. BACI is a product-level bilateral trade database maintained by the CEPII. Finally, we collect various country characteristics from the World Bank, the International Monetary Fund and a few other ancillary sources. We present summary statistics in Table 1. We follow about 30000 firms for 17 years including firms that enter late or exit early in our sample.

Table 1: Firm characteristics

Outcome Variables	Mean	Std.Dev.	P25	P50	P75
Δ Capital$_{s,t}$	0.022	0.536	-0.156	-0.032	0.119
Δ Tangible K$_{s,t}$	0.011	0.536	-0.196	-0.048	0.133
Δ Intangible K$_{s,t}$	0.021	0.920	-0.141	0.000	0.048
Δ Employment$_{s,t}$	0.086	0.346	0.000	0.051	0.167
Δ White-collars$_{s,t}$	0.020	0.443	-0.105	0.000	0.167
Δ Blue-collars$_{s,t}$	0.005	0.417	-0.105	0.000	0.118
Control Variables					
Log Total Assets$_{s,t}$	15.040	1.735	13.835	14.876	16.064
Log K$_{s,t}$	12.658	2.111	11.302	12.575	13.947
Log L$_{s,t}$	3.241	1.385	2.303	3.135	4.007
Log Total Sales$_{s,t}$	15.101	1.667	13.959	14.964	16.097
Log Value Added$_{s,t}$	13.989	1.590	12.950	13.908	14.914
Log Productivity$_{s,t}$	10.736	0.592	10.433	10.725	11.034
Log Debt$_{s,t}$	14.076	1.716	12.894	13.904	15.090
$\frac{CashFlow_{s,t}}{A_{s,t-1}}$	0.084	0.146	0.017	0.057	0.112
Leverage$_{s,t}$	1.762	3.361	0.387	0.728	1.453
Age$_{s,t}$	21.723	13.820	11.000	19.000	31.000
$\sharp$ Dest$_{s,t}$	9.686	14.140	1.000	4.000	12.000
$\frac{ForeignSales_{s,t}}{TotalSales_{s,t}}$	0.196	0.251	0.007	0.081	0.301
Variables of Interest					
Demand$_{s,t}$	0.002	0.017	-0.000	0.000	0.002
Demand Uncertainty$_{s,t}$	0.140	0.304	0.016	0.043	0.120
d Demand Uncertainty$_{s,t}$	0.011	0.634	-0.104	-0.002	0.089
Observations	446590				

NOTES: All outcome and control variables are computed using either fiscal (FARE, FICUS), social (DADS) or customs databases.
Δ Capital$_{s,t}$ is the log difference of the stock of non financial capital assets net of depreciation. Δ Employment$_{s,t}$ is the log difference of the number of employees (fiscal data). Δ Hourly Wage$_{s,t}$ is the log difference of the firm average hourly wage. Log Productivity$_{s,t}$ is the log value added per worker. Log K$_{s,t}$ is the log of tangible assets. Log L$_{s,t}$ is measured in full-time equivalent workers at the end of the year. $\frac{CashFlow_{s,t}}{A_{s,t-1}}$ is the cash flow measured by operating income over lagged total assets. Leverage$_{s,t}$ is the leverage ratio measured by debt over equity. Log Debt$_{s,t}$ is the log of total debt liabilities. Age$_{s,t}$ is in years. $\frac{ForeignSales_{s,t}}{TotalSales_{s,t}}$ is the share of exports relative to total sales. $\sharp$ Dest$_{s,t}$ is the number of foreign markets serviced by the firm. The variables of interest are computed using the bilateral product level database BACI. See Section 2.2 for the construction of the moments of the distribution of demand shocks. s and t index firms and years respectively.

2.2 Demand shocks and Uncertainty

The first step is to isolate demand shocks in the bilateral trade data. We follow a methodology similar to Garin et al. (2017) and Esposito (2018). We have a set of countries J that import a set of products P from a set of countries $I \setminus \{i = FRA\}$. Let $V_{p,i,j,t}$ be the imports of product p from country i by country j in year t and $\Delta V_{p,i,j,t}$ be its log 1st difference. Then $\upsilon_{p,i,j,t}$ is the idiosyncratic demand shock, computed as the residual of estimating the following equation country by country:

$$\begin{aligned} \Delta V_{p,i,j,t} = & \underbrace{\beta_1^j \Delta V_{p,i,t} + \beta_2^j \Delta V_{p,j,t} + \alpha_{j,t}^j}_{\text{Market Fundamentals}} \\ & + \underbrace{\alpha_{p,i,j}^j}_{\text{Bilateral Product Trend}} \\ & + \underbrace{\upsilon_{p,i,j,t}}_{\text{Idiosyncratic Demand Shock}} \end{aligned} \tag{1}$$

The intuition behind this 1^{st} stage is the following[1]. The fixed effect $\alpha_{p,i,j}^j$ removes any bilateral product trend that could generate increasing dispersion within an industry while being perfectly "certain". For instance, it controls for heterogeneity between technologies: demand for old products may decline relatively to new ones. The two aggregate growth rates can be thought off as the market fundamentals on the demand and supply side for any particular year and product. $\Delta V_{p,j,t}$ controls for the growth rate of imports of product p from the rest of the world by country j. We are interested in the specific demand from j to i relative to that aggregate fluctuation. All other things equal, the greater the residual $\upsilon_{p,i,j,t}$, the more j wants p from i as opposed to p from the rest of the world $I \setminus \{i\}$. $\Delta V_{p,i,t}$ controls for the growth of exports of i of p to the rest of the world. All other things equal, if i gets better at producing p, the residual

[1] This step can also be thought of as a generalization of the estimation of liquidity shocks in Khwaja and Mian (2008).

will be smaller. It therefore controls for supply shocks in i. The $\alpha^{j}_{j,t}$ fixed effect controls for aggregate conditions in the importing country j in year t.

The residuals $\upsilon_{p,i,j,t}$ are by construction the variance that cannot be explained by either the relevant trend or market fundamentals. Their first moment corresponds to the intensity of the demand signal originating from that market. Their dispersion then tells us its noisiness, that is how uncertain the signal would appear to an outside observer. We use this variable as our time and country varying proxy for demand uncertainty. We compute the mean ($D^{M1}_{k,j,t}$) for each sector-import-year. $P_{p\in k,i,t}$ is a counter for the number of non-zero trade flows in that triplet. Let $\upsilon^{p}_{k,j,t}$ be the p^{th} percentile of the distribution of all $\upsilon_{h,i\neq FRA}$ for each sector-importer-year (k, j, t). Let $D^{M2}_{k,j,t}$ be the 2^{nd} moment of the distribution of the idiosyncratic demand shocks of product p from sector k in country i (excluding France) into country j:

$$\text{Mean: } D^{M1}_{k,j,t} = \frac{1}{P_{p\in k,i,t} - 1} \sum_{i\neq FRA, p\in k} \upsilon_{p,j,i,t} \tag{2}$$

$$\text{Dispersion: } D^{M2}_{k,j,t} = \upsilon^{75}_{k,j,t} - \upsilon^{25}_{k,j,t} \tag{3}$$

This step provides robust and fairly intuitive measures of the shape of the distribution of demand shocks. The higher $D^{M1}_{k,j,t}$, the more intense the signal from that market. The higher the value of $D^{M2}_{k,j,t}$, the wider the distribution and the nosier the signal. We compute alternative measures using the spread between $\upsilon^{10}_{k,j,t}$ and $\upsilon^{90}_{k,j,t}$ or $\upsilon^{5}_{k,j,t}$ and $\upsilon^{95}_{k,j,t}$ and confirm that our results are virtually the same.

We now transform our sector-country-year measures into firm-year specific variables. We follow the standard method in the literature (See Aghion et al. (2017), Mayer et al. (2016) or Berthou and Dhyne (2018)). We weight each of our demand distribution variable by the firm initial market share and export intensity. The weights are necessary to account for the across firms variations in market diversification. However by using the initial firm weights, we ensure that any across time fluctuations are only caused by variations of the demand distribution measures and not by any endogenous firm reaction. In equation (4), we first weight our measures on the initial share of country j in firm f export portfolio ($\frac{X_{j,f,t_0}}{X_{f,t_0}}$). We then average this firm-destination level weighted variable across the export portfolio of firm f (J^f). Finally, we weight this measure over the initial export intensity of the firm (computed as Foreign Sales (X^*_{f,t_0}) over Total Sales (Y^*_{f,t_0}).

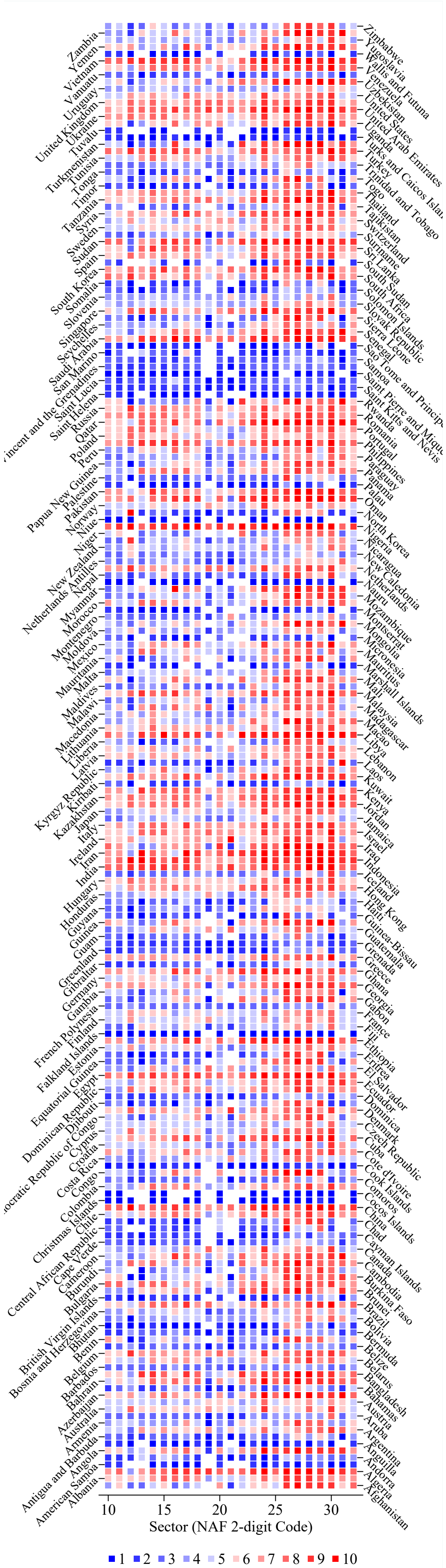
$$D^{M\{1,2\}}_{f,t} = \underbrace{\frac{X^*_{f,t_0}}{Y^*_{f,t_0}}}_{\text{Export Intensity}} \left(\frac{1}{J^f}\right) \sum_{j=1}^{J^f} \left(\underbrace{\frac{X_{j,f,t_0}}{X_{f,t_0}}}_{\text{Country Weight}} D^{M\{1,2\}}_{k=k_f,j,t} \right) \tag{4}$$

2.3 Stylized Facts

Table 2 reports the 10 highest value of Demand Uncertainty in our sample. The country sector with the highest value is the manufacture of coke and petroleum in Nigeria in 2010. It coincides with the death of the sitting president and the beginning of the first major terror attacks by Boko Harram. The next two values are Manufacture of other transport equipment in Iran 1997 (two massive earthquakes and a presidential election) and Rwanda 2010 (contested presidential election). In Figure 1, we plot the median value of the time series of each sector-by-country panel. The color of the cell indicates the decile of uncertainty the country-sector belongs to. Bright red indicates higher uncertainty and dark blue low uncertainty. Some countries like Iran or Irak have a high demand uncertainty across most of their sectors while others like most island nations have typically low demand uncertainty. Sectors like the machine manufacturing industry (28), the car industry (29) and transport equipment industry (30) usually exhibit high uncertainty across countries (See A.0.3 for a list of all manufacturing sectors). There is however plenty of variations within country or within sector.

In Figure 2a, we plot the distribution of those idiosyncratic demand shocks for the car industry ($k = 29$) for four countries (USA, Germany, Colombia and China). We see that demand

Figure 1: Heatmap of the median value of demand uncertainty by sector and country



NOTE: See Section 2.2 for the construction method and the appendix for the description of the NAF sectors.

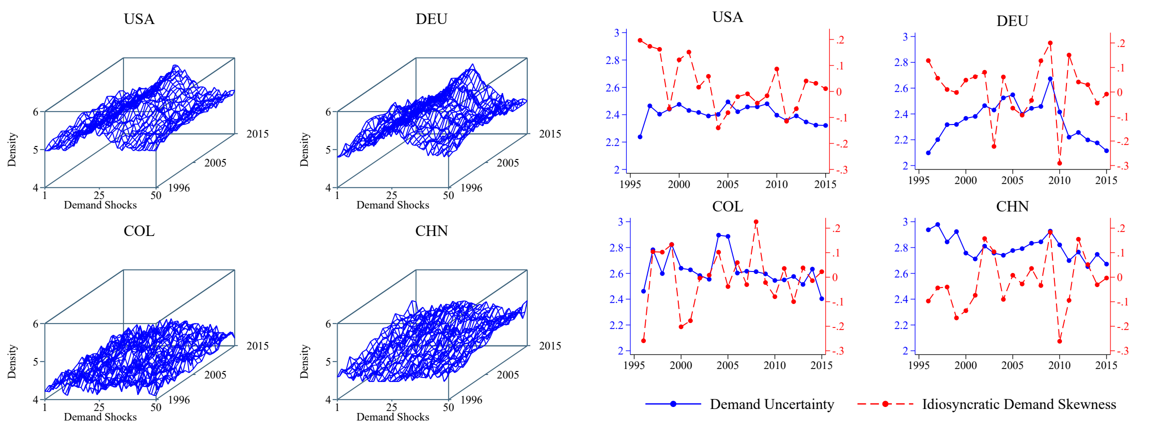
Table 2: Top 10 uncertain markets

	$D^{M2}_{k,j,t}$
1996 - Yemen - Manufacture of paper and paper products	9.62
1997 - Iran - Manufacture of other transport equipment	10.42
2002 - Cameroon - Manufacture of wood and of products of woo (...)	9.74
2003 - Central African Republic - Manufacture of other trans (...)	9.87
2007 - Equatorial Guinea - Manufacture of wood and of produc (...)	9.83
2009 - Vanuatu - Manufacture of other transport equipment	9.86
2010 - Nigeria - Manufacture of coke and refined petroleum p (...)	13.31
2010 - Rwanda - Manufacture of other transport equipment	10.17
2013 - Mali - Manufacture of wood and of products of wood an (...)	9.86
2013 - Syria - Manufacture of other transport equipment	10.14

in the USA and Germany mostly follows a normal shaped density function while it fluctuates across time. Whereas demand from Columbia and China appears much noisier. We exploit those time and geographical variations in the uncertainty of demand shocks to identify them.

Figure 2: Time-varying distribution of demand shocks for the car industry (1996-2015)

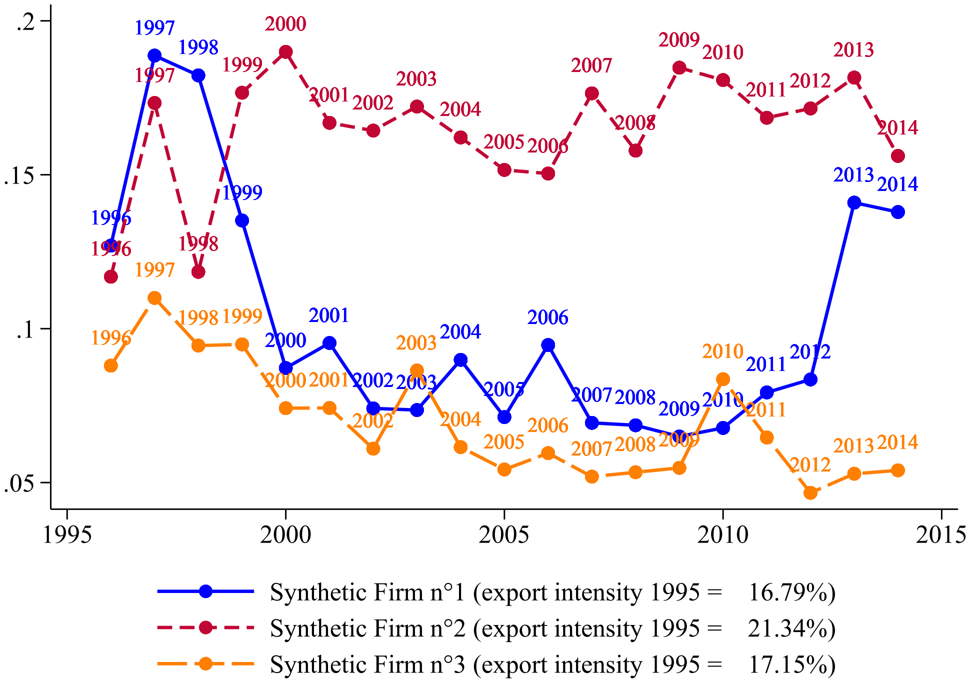
(a) 3d density plot **(b)** Dispersion and Skewness



NOTE: Those figures show the time-varying shape of the distribution of demand shocks in the car industry for four countries. The left sub-figure presents the density for every duo-percentile of the distributions of demand shocks (eg. 25 is the median) for every year. The right sub-figure shows the 2nd and 3rd moment of the same distributions. See Section 2.2 for the construction method.

To illustrate our firm-level measure of demand uncertainty, Figure 3 plots the time series of $D^{M2}_{f,t}$ for three synthetic firms. We see that because of their different initial exposure to foreign markets, each firm is experiencing a different evolution of demand uncertainty. Firm n^o1 and n^o2 experience a sharp increase in uncertainty around the time of the Asian and Russian

Figure 3: Firm Level Demand Uncertainty



NOTE: This figure shows our firm-level measure of demand uncertainty ($D^{M2}_{f,t}$) for three synthetic firms. In order to satisfy anonymity requirements, each point is computed as the average value of uncertainty for 10 firms selected based on their closeness to the sample mean in terms of size and growth.

crisis. n^o2 then deals with high uncertainty throughout the entire period. Meanwhile, firm n^o1's uncertainty returns to a more moderate level, with spikes around 2004, 2006 and 2013. Whereas, firm n^o3 exhibits a much lower level of uncertainty as well as lower volatility.

3 Impact of Demand Uncertainty on Firm Growth

In this section, we first provide estimates of the firm growth path around an increase in demand uncertainty using local projections. We then show how financial constraints and irreversibility compound the effect of uncertainty.

3.1 Baseline Regressions

We use the Local Projections (LP) method as in Jordà (2005) to recover the dynamic effect of demand uncertainty on firm growth. We estimate its impact at up to 8 years after the initial impulse and 6 years prior. Our variable of interest is the first simple difference of Demand Uncertainty: $dD^{M2}_{f,t}$. This variable has little auto-correlation. We show the absence of auto-correlation in Figure A.0.13 for the same three synthetic firms as in Figure 3. We confirm this in a more generalized way with the Auto-Correlation Function in Figure A.0.14). The weak auto-correlation $dD^{M2}_{f,t}$ allows us to measure the effect of a one time increase in uncertainty. Let:

$$G_{f,t} = \{Capital, Employment\}$$

then:

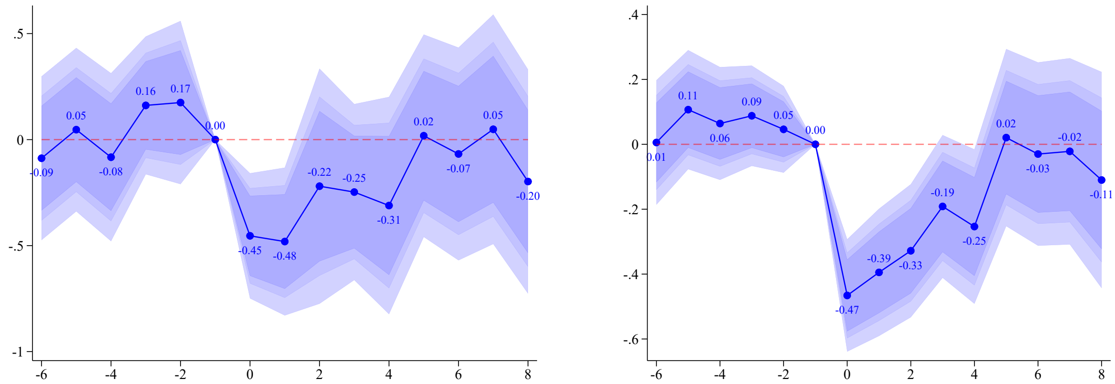
$$\Delta G_{f,t+h} = \log\Big(\frac{G_{f,t+h}}{G_{f,t-1}}\Big) = \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X_{f,t-1}} + \alpha_2^h D^{M1}_{f,t} + \beta_1^h dD^{M2}_{f,t} + \gamma^h_{k,t} + \gamma^h_f + \epsilon_{f,t+h} \tag{5}$$

for $h \in \{-6, 8\}$ and where $\Delta G_{f,t+h}$ denotes the cumulative change in outcome variable G from time t to $t + h$. We use the log difference as in Bloom et al. (2007). We add a vector of lagged controls $\mathbf{X_{f,t-1}}$ to capture relevant firm characteristics for investment (e.g. Gilchrist and Himmelberg (1995), Bloom et al. (2007) and Gala and Julio (2016)). By default, we include the log of $G_{f,t-1}$, the lagged growth rate and level of foreign sales and the lagged level of demand uncertainty ($D^{M2}_{f,t-1}$). We also control for the current foreign demand signal ($D^{M1}_{f,t}$). We add a firm fixed effect to capture the time-invariant heterogeneity of firm dynamics. Finally, we add a sector-time fixed effect to capture the sector business cycle. We cluster the standard errors at the firm-level to account for potential within firm serial correlation in the error term (Bertrand et al., 2004).

Figure 4 shows the effect of a one-standard deviation increase from the mean value of $dD^{M2}_{f,t}$ for investment and employment relative to the year before the shock. Both outcomes exhibit little anticipatory response to the shock. On the left panel of Figure 4, the impact on the stock of non financial capital is negative during the five years following the increase in uncertainty.

Figure 4: Demand Uncertainty and Firm Growth

(a) Investment **(b)** Employment



NOTE: Those figures present estimates of the coefficient $\beta_1^h * 100$ associated with demand uncertainty from estimating this equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}} \mathbf{X_{f,t-1}} + \alpha_2^h D^{M1}_{f,t} + \beta_1^h dD^{M2}_{f,t} + \gamma^h_{k,t} + \gamma^h_f + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the firm-level, are displayed in shades of blue. The size of the shock is set at one standard deviation. E.g.: a one standard deviation uncertainty shock decreases investment growth by 0.45 percentage point the year of the shock.

However, only the first two years are significantly different from zero. It then reverts back to approximately zero until the end of the eight-year window. A standard deviation size increase in uncertainty results in a contemporaneous 0.45 percentage point lower growth rate of investment (compared to a sample mean growth rate of 2.2%). Four years later, this increase still results in a 0.31 p.p. lower growth rate. The effect on employment growth is negative until the fifth year while it slowly reverts back to zero. It then remains at zero until the end of the time-window. The contemporaneous effect is equal to 0.47 percentage point lower growth rate (compared to a sample mean of 8.6% and an effect of -0.25 p.p. four years later).

Figure A.0.15 presents the result from the same specification on other outcome variables. The effect on tangible investment is stronger than the effect on intangible. The effect on debt growth follows a very similar pattern as the effect on investment. We confirm the pattern and magnitude of our result on employment by using data from the DADS social declarations rather than from the fiscal declarations. We also find that the employment of white-collar workers is somewhat more sensitive to uncertainty than the employment of blue-collar workers.

This persistent negative effect from a one time increase in uncertainty contrasts with the wait-and-see effect predicted by the literature. We now examine two potential explanations. In the next section, we show that this persistence is partially explained by firms facing financial constraints prior to the shock. Then, we present results indicating that differences across firms in the irreversibility of the growth decision is also driving some of the dynamic of the effect of uncertainty.

3.2 Persistent Effect of Uncertainty under Financial Constraint

As we are interested in how firm-level financial frictions may change the firm response to uncertainty and explain the persistence of its effect, we interact our variable of interest with two different measures indicating that the firm was financially constrained in the previous period. The ability to generate cash-flow is a strong indicator of the ability to self-finance growth or access external financing (Gala and Julio, 2016). Additionally, cash-flows can be used as insurance against future shocks. The more financially constrained a firm is, the stronger and more persistent its reaction to demand uncertainty should be. If a firm fears that drawing a bad demand shock could lead to its default then its return on the option of waiting is higher. It should therefore increase the effect of uncertainty. We estimate the following equation:

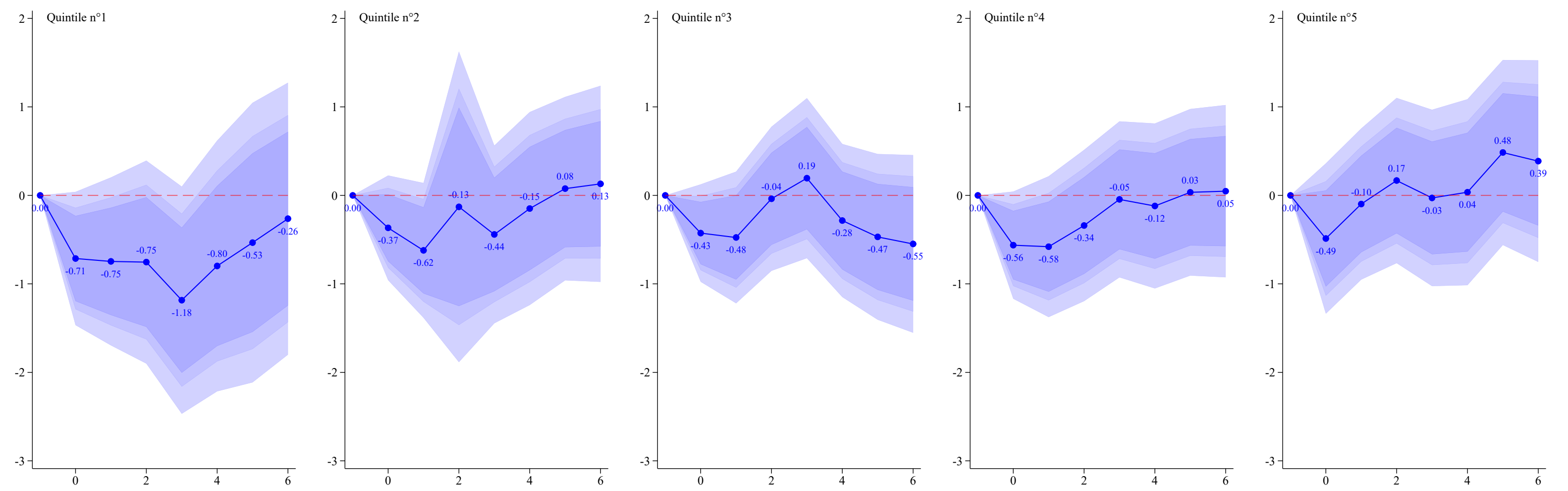
$$\begin{aligned}\Delta G_{f,t+h} = {} & \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X}_{\mathbf{f},\mathbf{t}-\mathbf{1}} + \alpha_2^h D_{f,t}^{M1} \\ & + \beta_1^h dD_{f,t}^{M2} + \beta_2^h (dD_{f,t}^{M2} \times CF_{f,t-1}) + \beta_3^h CF_{f,t-1} \\ & + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}\end{aligned} \tag{6}$$

In Figure 5, we present the effect of demand uncertainty at various levels of the cash-flow distribution. We use lagged cash-flow normalized over lagged assets trimmed at the 0.5 and 99.5 percentile. It excludes any observation where this measure is bellow -47% and above 46%. We then follow the methodology detailed by Hainmueller et al. (2019). We allow the coefficient β_2^h to vary across each quintiles of lagged cash-flow over assets. We then show the effect of a standard deviation uncertainty shock estimated at the median of each quintile. We focus once again on investment (first row) and employment (second row). The lower the quintile, the more financially constrained the firm is.

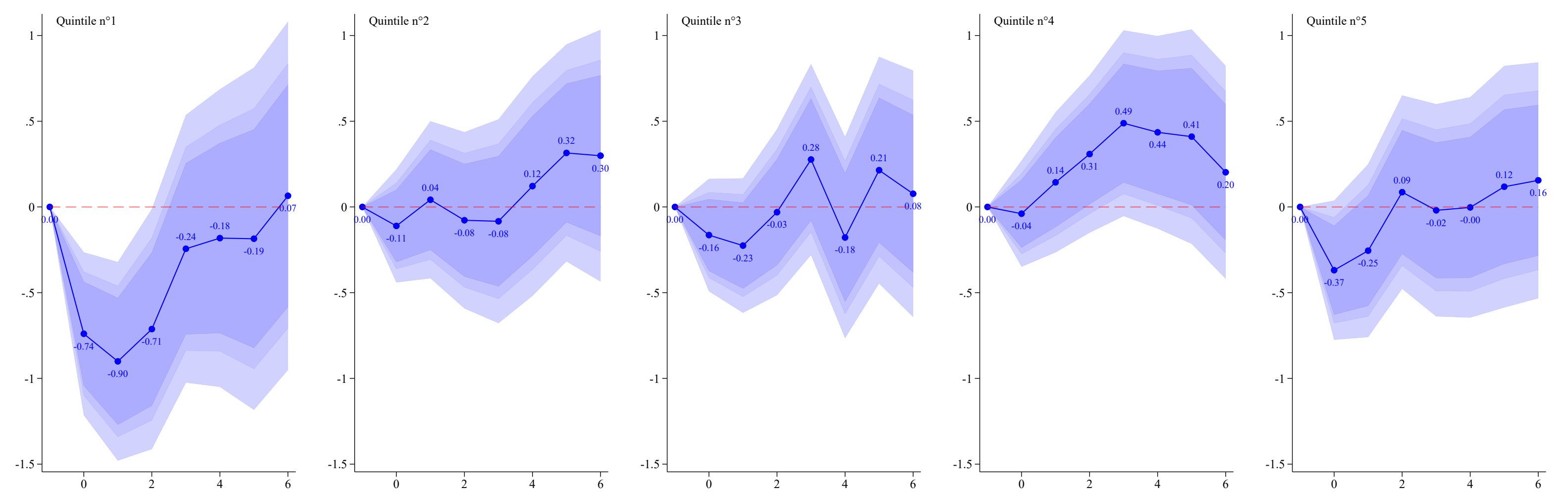
Figure 5: Demand Uncertainty and Cash Constraint

High ⟶ Low

(a) Investment



(b) Employment



NOTE: Those figure present estimates of β_2^h from estimating this equation: $\Delta G_{f,t+h} = \alpha_1^h \mathbf{X_{f,t-1}} + \alpha_2^h D_{f,t}^{M1} + \beta_1^h dD_{f,t}^{M2} + \beta_2^h (dD_{f,t}^{M2} \times CF_{f,t-1}) + \beta_3^h CF_{f,t-1} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the firm-level, are displayed in shades of blue.

When we allow the coefficients β_2^h to vary depending on the firm ability to generate cash-flow, we find that the most financially constrained firms experience a somewhat sharper and longer slowdown. The contemporaneous effect on investment is moderately bigger (-0.71 vs -0.49 p.p. for the bottom and top quintile respectively) Firms in the lowest quintile are still 1.18 percentage p.p. bellow their counter-factual investment growth rate 3 years after the shock. Meanwhile, firms in the rest of the distributions are no longer suffering any effects. For employment growth, losses appear once again to be concentrated in the lowest quintile. The contemporeneous effect is -0.74 p.p. for the 1st quintile versus approximately 0 for the next three quintiles and -0.37 for the top quintile. Whereas the impact either reverts back to 0 or turns positive for the top 4 quintiles, it remains negative for at least 3 periods for the bottom bin of the cash-flow distribution.

The ability to generate cash flow only represents one facet of being financially constrained. To investigate further, we repeat the same exercise for the firm's stock of debt. We divide all firms in 5 quintiles based on their ex-ante debt-to-asset ratio. We trim the ratio at the 99.5 percentile level. It excludes any observations with a ratio above 153% . We then estimate the following equation:

$$\begin{aligned}\Delta G_{f,t+h} &= \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X}_{\mathbf{f,t-1}} + \alpha_2^h D_{f,t}^{M1} \\ &\quad + \beta_1^h dD_{f,t}^{M2} + \beta_2^h (dD_{f,t}^{M2} \times DA_{f,t-1}) + \beta_3^h DA_{f,t-1} \\ &\quad + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}\end{aligned} \tag{7}$$

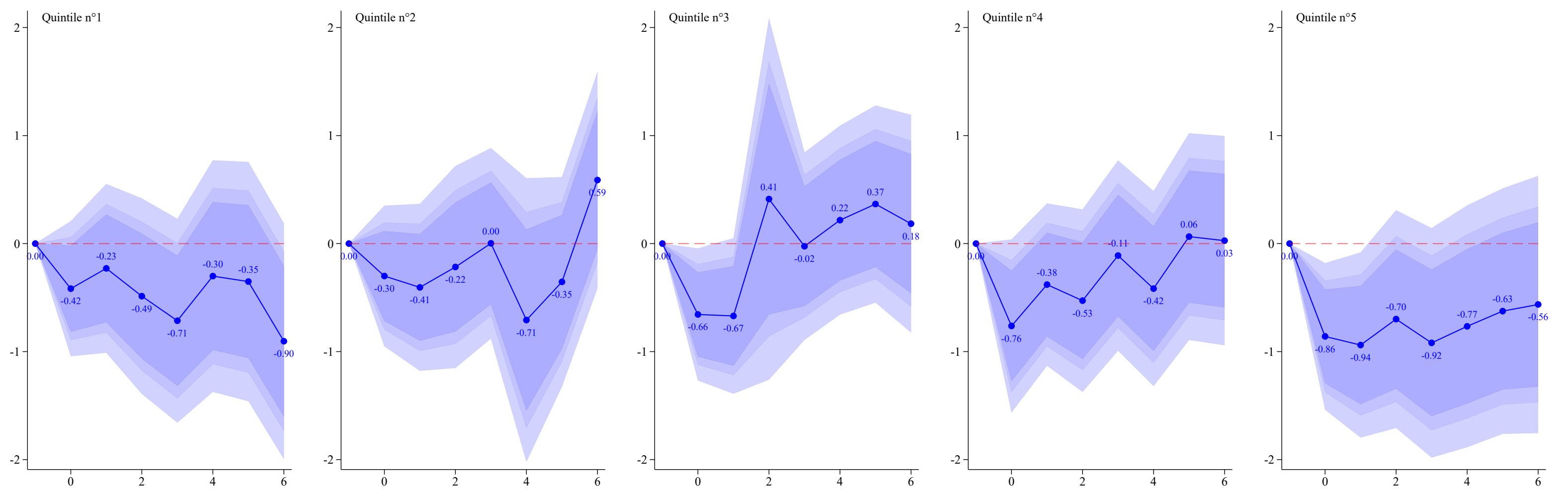
and we plot the results in Figure 6. The higher the quintile, the more financially constrained the firm is. The investment of firms in the 1st two bins experiences a contemporaneous effect that is lower than the sample average estimated earlier (-0.42 and -0.30 vs -0.45 p.p.) whereas firms in the next three bins experience losses ranging from 0.66 to 0.86 percentage point. Moreover, the investment of firms in the highest debt-to-asset bin has not recovered by the end of the 6-year window. The employment growth of firms in the lowest bin does not suffer. Firms in the next two bins suffer some contemporaneous losses but mostly recover by the 2nd year after the shock. Firms in the top two bins suffer severe losses (from -0.33 to -0.55 p.p.) for 2 to 3 years. The effect then dies out in the following years unlike for investment.

Controlling for various forms of financial constraints does not reduce the estimated effect of uncertainty by any substantive amount. However, the response to uncertainty does exhibit strong non-linearity along either the debt or cash to asset ratio. The contemporaneous response is usually barely distinguishable from zero for low constraints firms and does not exhibit any persistence. Those results support the view that financial frictions are at least one of the reasons behind the lack of a rebound effect expected after the resolution of an uncertainty shock.

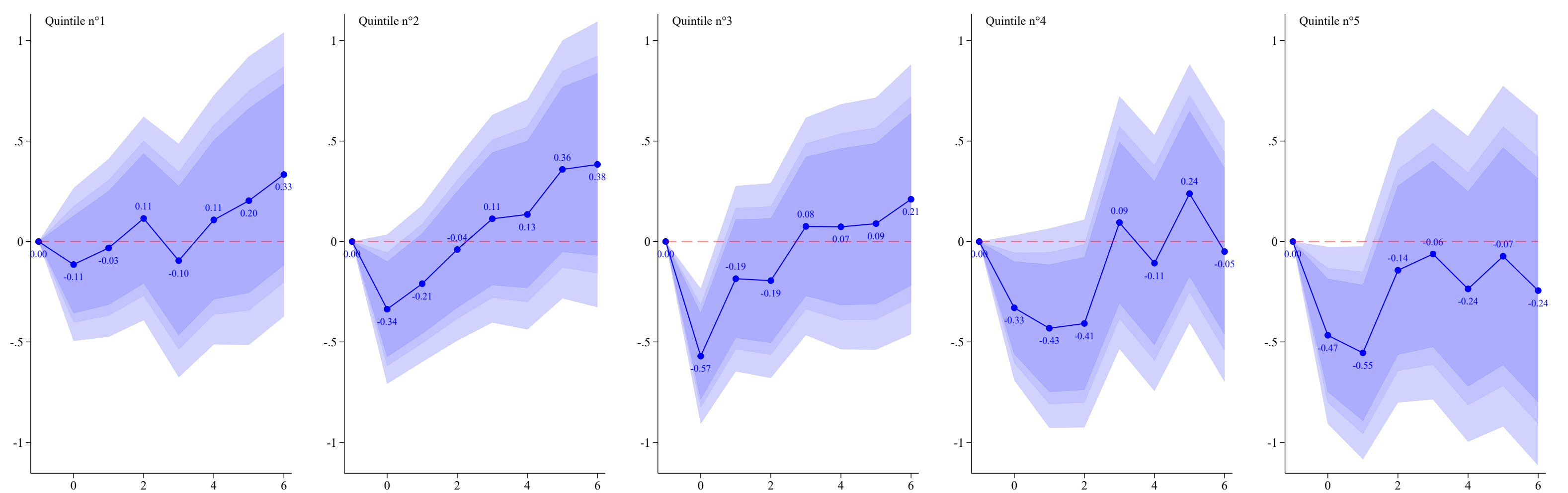
Figure 6: Demand Uncertainty and Debt Constraint

Low → High

(a) Investment



(b) Employment



NOTE: Those figures present estimates of β_2^h from estimating this equation: $\Delta G_{f,t+h} = \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X_{f,t-1}} + \alpha_2^h D^{M1}_{f,t} + \beta_1^h dD^{M2}_{f,t} + \beta_2^h(dD^{M2}_{f,t} \times DA_{f,t-1}) + \beta_3^h DA_{f,t-1} + \gamma^h_{k,t} + \gamma^h_f + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the firm-level, are displayed in shades of blue.

3.3 Sectoral Comovement and the Persistent Effect of Uncertainty

Another potential explanation to the persistence of the effect of an uncertainty shock lies in the degree of reversibility of the decision to grow. The more irreversible the decision to grow is, the higher the return on the option of waiting and the stronger the initial impact of uncertainty should be. Firms that are positively correlated with their sector will find it harder to sell or buy on the secondary market. All firms in that sector are also more likely to face the same uncertainty. Therefore no firms should be able to take advantage of this situation to acquire market shares. In such a situation, an uncertainty shock may even trigger a sector-wide downturn. The persistence of the estimated effect of the 2^{nd} moment shock may include the 1^{st} moment of the second round effects. Firms with a negative correlation to their sector should benefit from having a low option value when facing uncertainty. At the same time, their competitors are less likely to face a similar uncertainty and should therefore be in a position to acquire market share at the expanse of the uncertain. This mechanism should prevent firm-level uncertainty from generating any aggregate fluctuations. Finally, firms that are neither positively or negatively correlated with their sector are both benefiting from a low option value of waiting and little risk of an uncertainty generated aggregate downturn.

We follow Guiso and Parigi (1999) to construct our measure of firm specific irreversibility IRR_f. We compute the correlation between the growth rate of the firm's domestic sales and the growth rate of the domestic sales of its industry. Formally, we compute for each firm-year the average of the growth rate of sales for all other firms in the industry. Then, we compute the pearson correlation coefficient $IRR_f = \rho(\Delta Y_{f,t}, \Delta Y_{k_f \setminus f,t})$. This measure is bounded between $\{-1, 1\}$ with 1 indicating a high irreversibility. As in the previous sections, we divide it in 5 quintiles and estimate the effect of uncertainty at the median of each quintile:

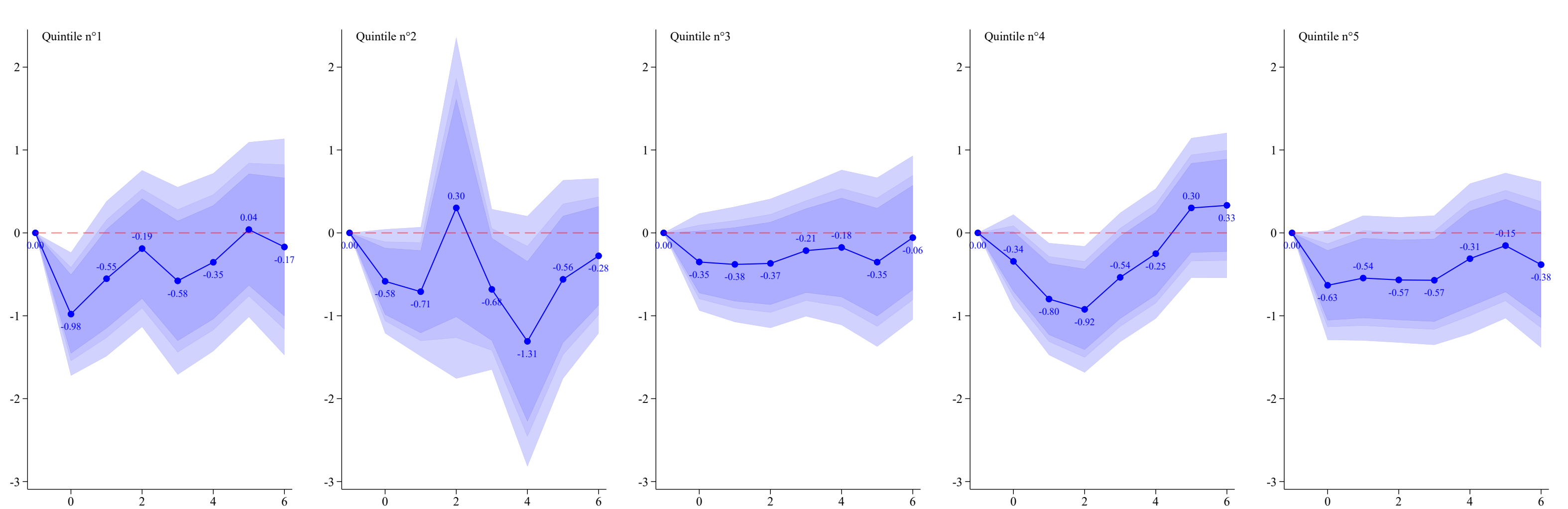
$$
\begin{aligned}
\Delta G_{f,t+h} = {} & \alpha_{\mathbf{1}}^{\mathbf{h}} \mathbf{X_{f,t-1}} + \alpha_2^h D_{f,t}^{M1} \\
& + \beta_1^h dD_{f,t}^{M2} + \beta_2^h (dD_{f,t}^{M2} \times IRR_f) + \beta_3^h IRR_{f,t-1} \\
& + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}
\end{aligned} \tag{8}
$$

Our measure of irreversibility is not time-varying so its direct effect is absorbed by the firm fixed effect. We plot the effect of its interaction with uncertainty in Figure 7. Three striking results emerge: (1) The investment and employment of firms with neither positive nor negative sectoral co-movement (quintile $n^o 3$) do not suffer much from an uncertainty shock, if anything they increase their employment in the longer run. (2) Firms with a negative correlation experience a negative contemporaneous impact that quickly reverts back to zero. (3) Firms with high sectoral correlation of their sales suffer from a more persistent slowdown. One explanation for this would be that in a highly-correlated sector, the cost of drawing a bad demand shock would be disproportionate as the firm would suspect that the other firms in the sector are drawing similarly bad shocks. A rise in its uncertainty would make the firm cautious of the risk of a sector-wide slowdown. In fact, if the other firms in the industry act in a similar fashion, it might trigger the slowdown and make it sharper and longer.

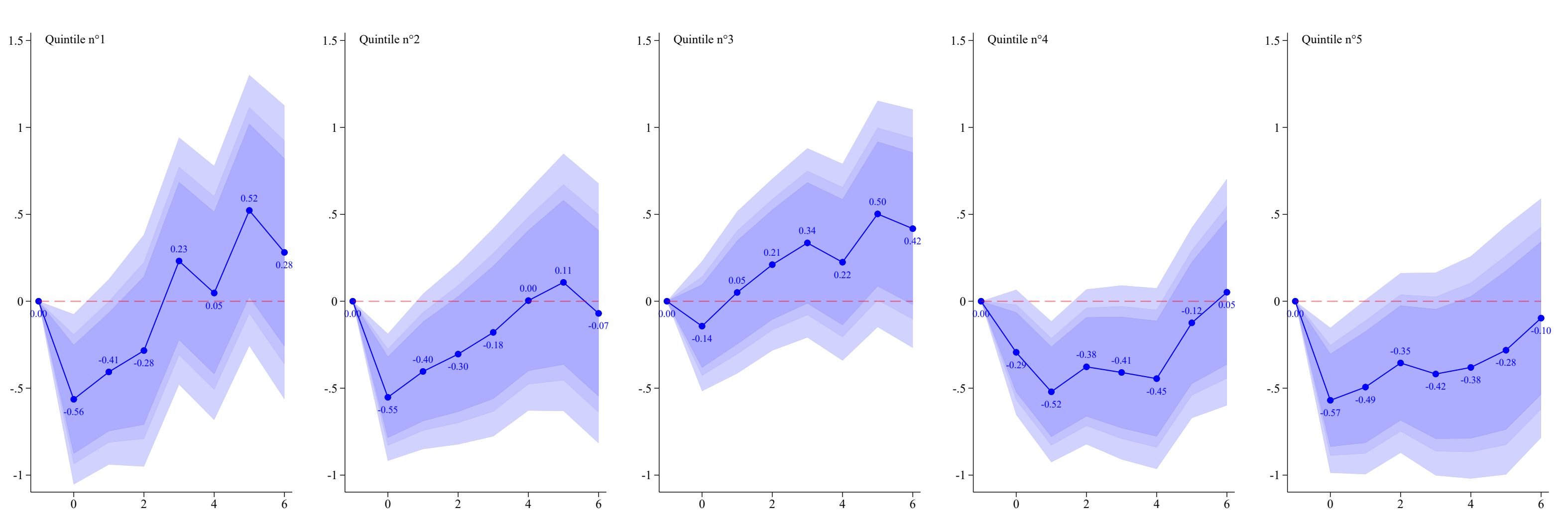
Figure 7: Demand Uncertainty and Sectoral Comovement

Negative ⟶ Zero ⟶ Positive

(a) Investment



(b) Employment



NOTE: Those figures present estimates of β_2^h from estimating this equation: $\Delta G_{f,t+h} = \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X_{f,t-1}} + \alpha_2^h D_{f,t}^{M1} + \beta_1^h dD_{f,t}^{M2} + \beta_2^h (dD_{f,t}^{M2} \times IRR_f) + \beta_3^h IRR_{f,t-1} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the firm-level, are displayed in shades of blue.

4 Robustness

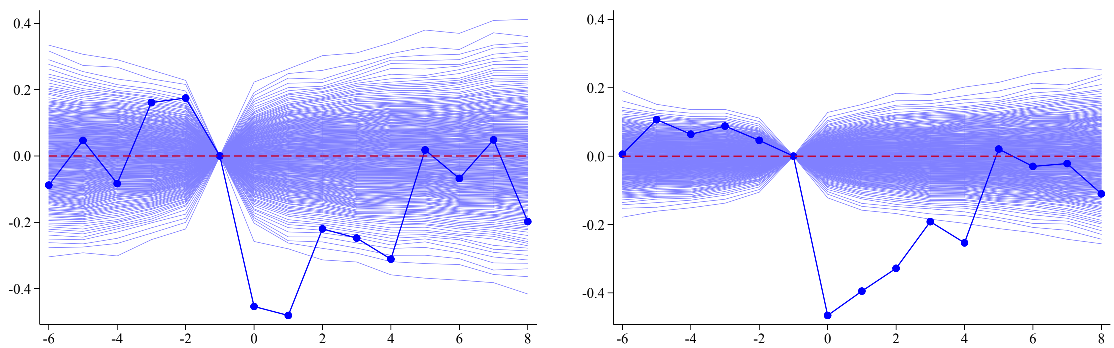
4.1 Placebo Inference

In the baseline specification, we clustered standard errors at the firm level. This provided us with standard errors that are asymptotically robust to serial auto-correlation in the error term. Here we implement Chetty et al. (2009)'s non-parametric permutation test[2] of $\beta_1^{h>0} = 0$.

To do so, we randomly reassign the uncertainty time serie across firms and then we re-estimate the baseline regression. We repeat this process 2000 times in order to obtain an empirical distribution of the placebo coefficients $\hat{\beta}_1^{h,p}$. If demand uncertainty had no effect on firm growth, we would expect our baseline estimate to fall somewhere in the middle of the distribution of the coefficients of the placebo coefficients $\hat{\beta}_1^{h,p}$. Since that test does not rely on any parametric assumption regarding the structure of the error term, it is immune to the over-rejection of the null hypothesis highlighted by Bertrand et al. (2004).

Figure 8: Distribution of Placebo Estimates

(a) Investment **(b)** Employment



NOTE: Those figures present each half percentile of the distribution of 2000 estimates of the coefficient $\hat{\beta}_1^{h,p}$ of Demand Uncertainty after performing a random permutation.

We plot the distribution of the placebo coefficients in Figure 8. The figure confirms that our coefficients of interest $\beta_1^{h>0}$ (the blue connected markers) lie outside of the [p0.5,p99.5] interval (the light blue lines) of the distribution of placebo coefficients. Meanwhile, the estimates of

[2]See Malgouyres et al. (2018) for a more recent application

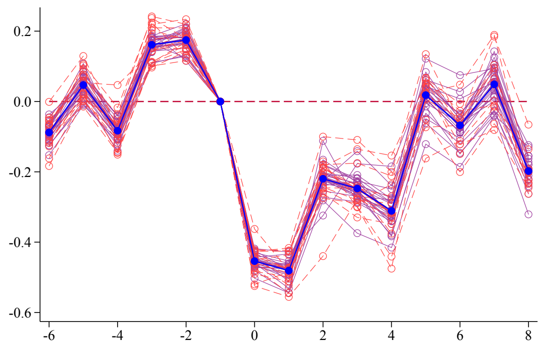
$\beta_1^{h<0}$ fall within the bounds of the distribution of placebos, albeit narrowly so in some cases. This exercise confirms that uncertainty has a negative effect on firm growth.

4.2 Sensitivity

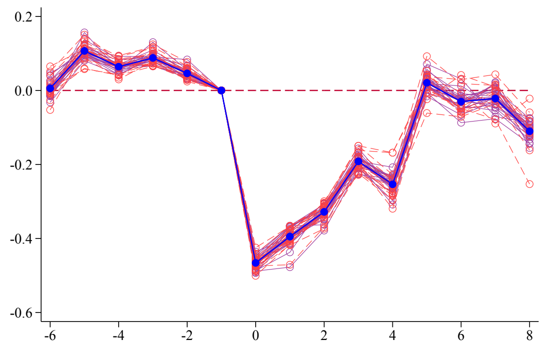
Since our sample includes events such as the Great Financial Crisis (2008 and 2009), we wish to check whether our results are robust to the omission of any particular year. We run the same baseline regressions while omitting turn by turn any year between 1996 and 2013. We plot the results in Figure 10 in red. We find results that are quantitatively and qualitatively the same as on the full sample. It shows that our specification satisfyingly accounts for the complex dynamics of our sample period. We repeat this procedure for the sectors and plot the results in purple in figure 10. This estimate is also statistically highly significant and robust to taking out any sectors (NAF 2 digit). Finally, we also demonstrate that this estimate is robust to the inclusion of various observable characteristics in Figure 9.

Figure 9: Sensitivity to sample selection

(a) Investment



(b) Employment



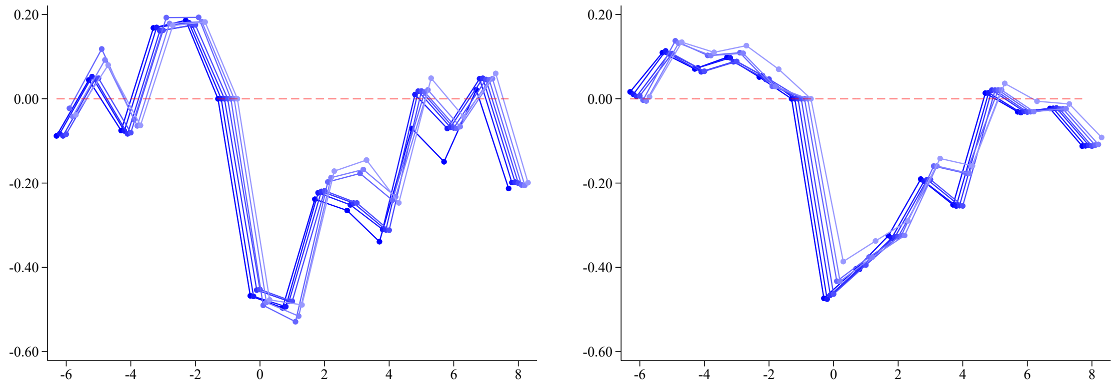
NOTE: Those figures present estimates of the coefficient β_1 of Demand Uncertainty after subtracting either a year or a sector at a time. We estimate the following equation: $\Delta G_{f,t+h} = \alpha_{\mathbf{1}}^{\mathbf{h}} \mathbf{X_{f,t-1}} + \beta_1^h dD_{f,t}^{M2} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$.

4.3 Validation

To validate our measure of demand uncertainty, we check that an increase in demand has an effect on firm growth. Given the existing literature on exports dynamics and productivity, we

Figure 10: Sensitivity to different specifications

(a) Investment **(b)** Employment



NOTE: Those figures present estimates of the coefficient β_1 of Demand Uncertainty after adding one extra control variable at a time. We estimate the following equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}}\mathbf{X_{f,t-1}} + \beta_1^h dD^{M2}_{f,t} + \gamma^h_{k,t} + \gamma^h_f + \epsilon_{f,t+h}$. and add one of the following variable at a time: $D^{M1}_{f,t}$, Lagged Cash-flow to asset ratio, a dummy variable indicating whether the firm belongs to a group, lagged debt to asset ratio, lagged sales to asset ratio and lagged productivity.

suspect that the average firm's response is not linear. We therefore regress firm capital and employment growth on the 1^{st} moment of foreign demand shocks interacted with lagged productivity (value-added over employees). We estimate the following equation:

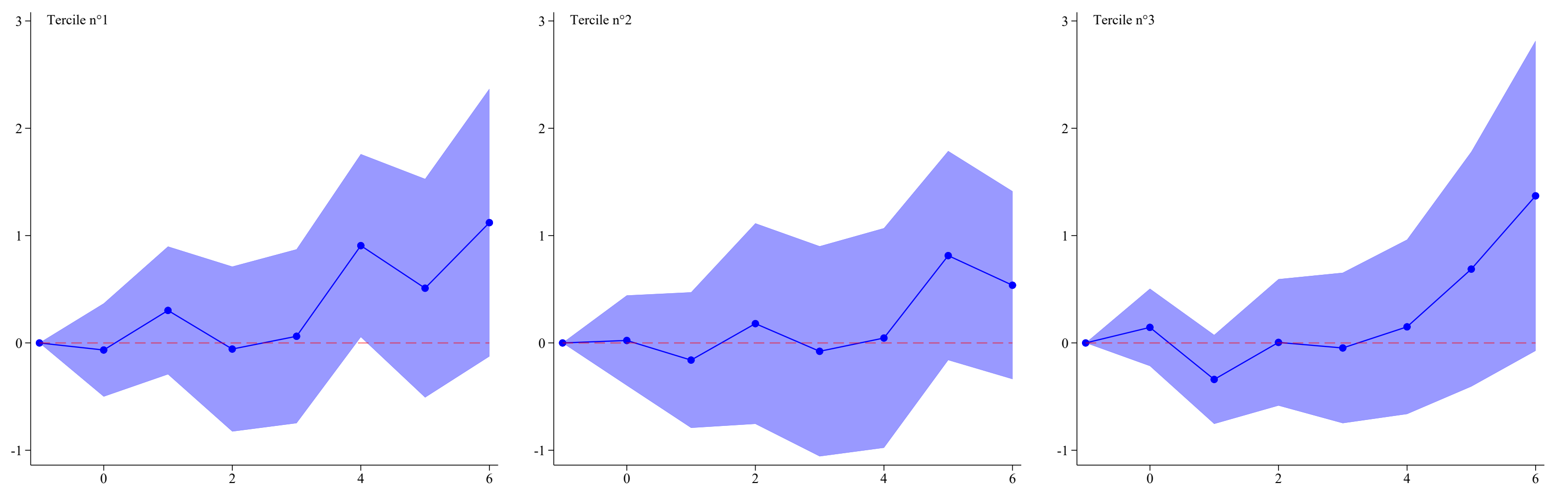
$$G_{f,t+h} = \alpha_1^{\mathbf{h}}\mathbf{X_{f,t-1}} + \alpha_2^h D^{M1}_{f,t} + \alpha_3^h (D^{M1}_{f,t} \times PROD_{f,t-1}) + \beta_3^h PROD_{f,t-1} + \gamma^h_{k,t} + \gamma^h_f + \epsilon_{f,t+h} \tag{9}$$

. We plot the results in Figure 11. The effect of a positive demand signal has little short-run effect for investment. In the longer run (4 to 6 years), we see a sizable increase (about 1 percentage point per year for all terciles). The effect on employment is more contrasted. The contemporaneous effect for firms in the lowest third of the productivity distribution is negative (about 1/3rd of a p.p.). The effect then reverts back to zero and becomes positive in the next 3 years with a low statistical significance. The effect for the middle tercile is negative but not significant for the first 2 years. It then becomes positive in the last 3 years. Firms with the highest productivity increase their employment throughout the entire window. This result matches the pattern highlighted by Aghion et al. (2018). We therefore establish that firms react in a consistent fashion to the 1^{st} moment of foreign demand shocks.

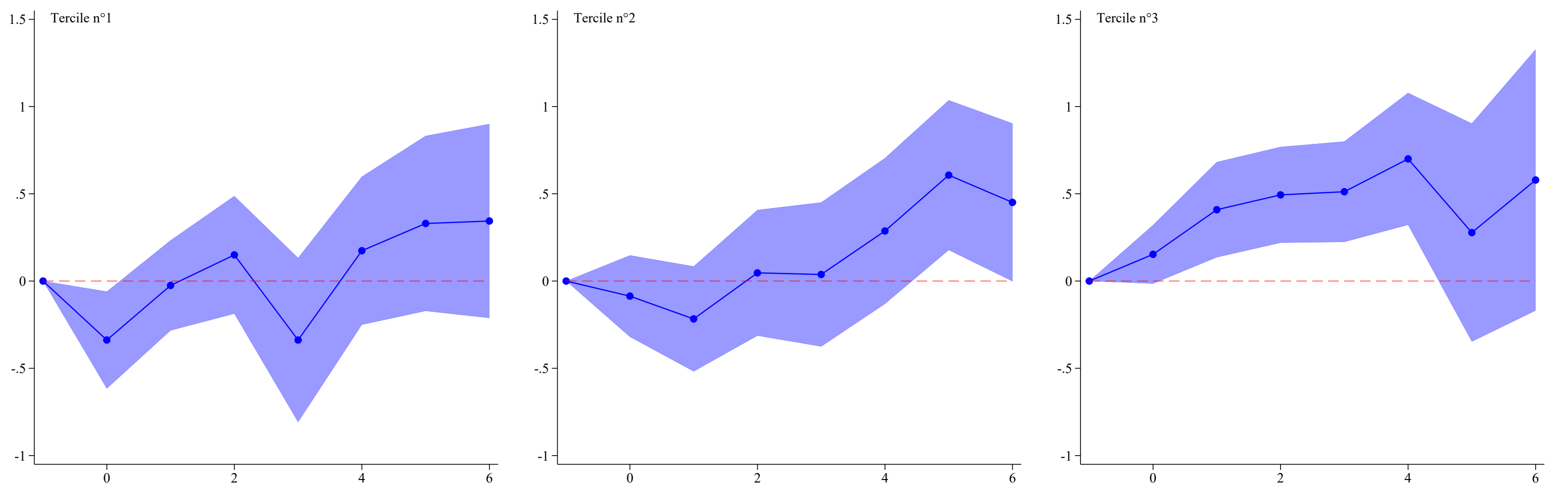
Figure 11: Firm Growth, Foreign Demand Signal and Productivity

Low ⟶ High

(a) Investment



(b) Employment



NOTE: Those figures present estimates of α_3^h from estimating this equation: $\Delta G_{f,t+h} = \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X_{f,t-1}} + \alpha_2^h D_{f,t}^{M1} + \alpha_3^h (D_{f,t}^{M1} \times PROD_{f,t-1}) + \beta_3^h PROD_{f,t-1} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. The 90% error band computed with robust standard errors clustered at the firm-level is displayed in blue.

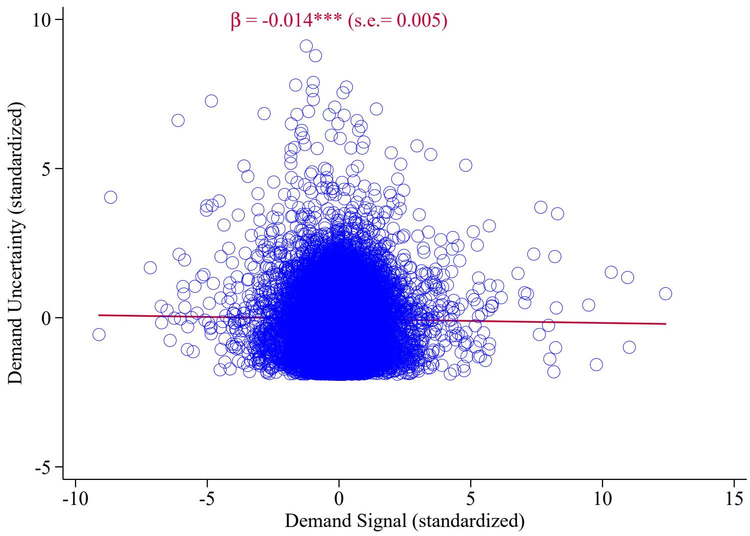
5 Conclusion

The increase in cross-border trade and financial linkages since the 1990's has led to a greater exposure of domestic agents to shocks abroad. More firms are now dependent on inherently uncertain demand conditions. In this paper, we investigate how the uncertainty around the realization of demand shocks affects the growth dynamic of French manufacturing firms between 1996 and 2013. We build a measure of demand uncertainty by computing the dispersion of estimated demand shocks from a highly dis-aggregated bilateral trade database. We then document the effect of an increase in demand uncertainty on employment and investment growth using French fiscal data. A striking result is the persistent negative effect of a one-time uncertainty shock. The effect lasts for up to 5 years for both investment and employment. It does not exhibit any evidence of post-shock compensation which makes those losses permanent. We find that losses are magnified for financially constrained firms and firms with high sales correlation with their sector.

Losses due to uncertainty are concentrated on the most financially constrained firms which suggests that aggregate losses may be rather modest. However, our results show much more persistent effect of uncertainty on the growth of firms than the temporary losses predicted by the real-option theory. Policies that help reduce firm financial and information frictions would therefore be an appropriate response to periods of high uncertainty by reducing permanent losses among financially constrained firms, assuming those constraints are not correlated to productivity. This implication seems particularly relevant given the current uncertainty around trade policy with the United-States and Great-Britain.

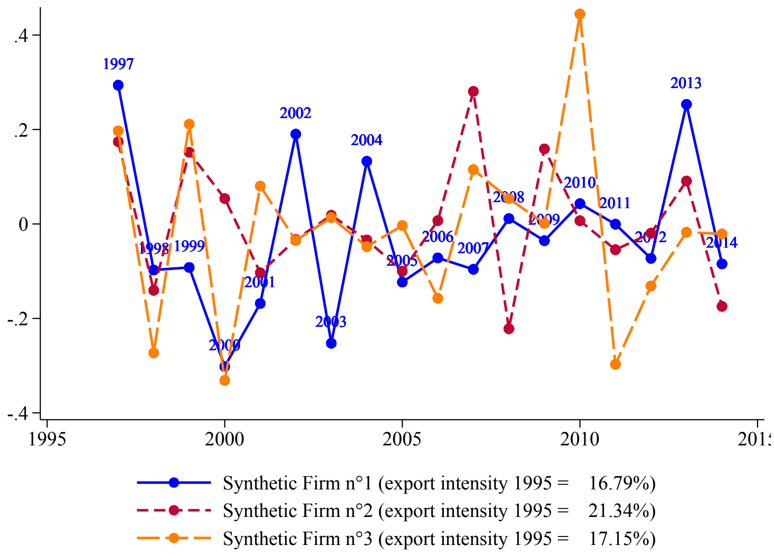
A Appendix

Figure A.0.12: Demand Signal to Noise



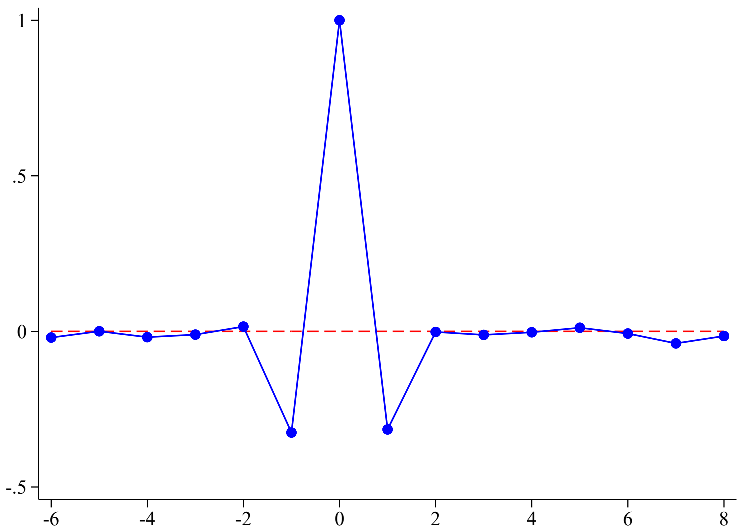
NOTE: This figure shows the correlation between the 1st and 2nd moment of the distribution of demand shocks. See Section 2.2 for the construction method.

Figure A.0.13: Firm Specific Demand Uncertainty - 1st difference



NOTE: This figures shows our firm-level measure of demand uncertainty ($D^{M2}_{f,t}$) for three synthetic firms. In order to satisfy anonymity requirements, each point is computed as the average value of uncertainty for 10 firms selected based on their closeness to the sample mean in terms of size and growth. See Section 2.2 for the construction method.

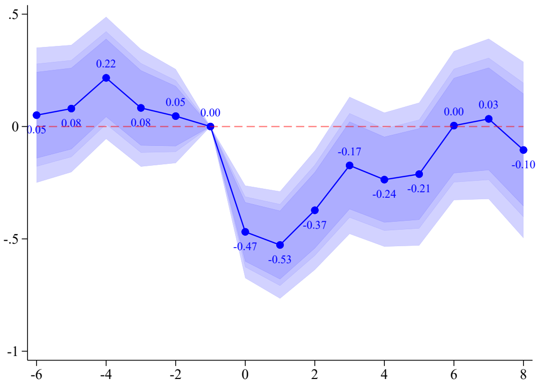
Figure A.0.14: Demand Uncertainty Shock Local Projection



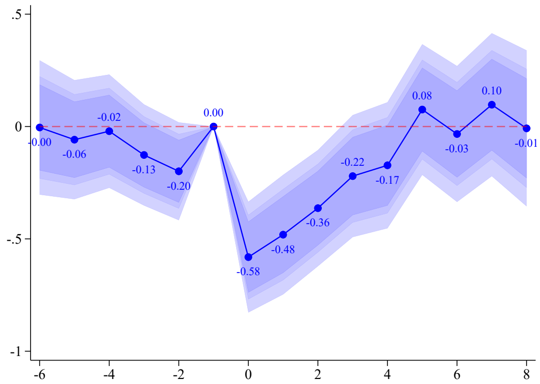
NOTE: This figure plots the coefficients β^h obtained from estimating the local projection of the first difference of Demand Uncertainty $dD^{M2}_{f,t+h} = \beta^h dD^{M2}_{f,t} + \gamma^h_{k,t} + \gamma^h_f + \epsilon_{f,t+h}$.

Figure A.0.15: Demand Uncertainty and Firm Growth

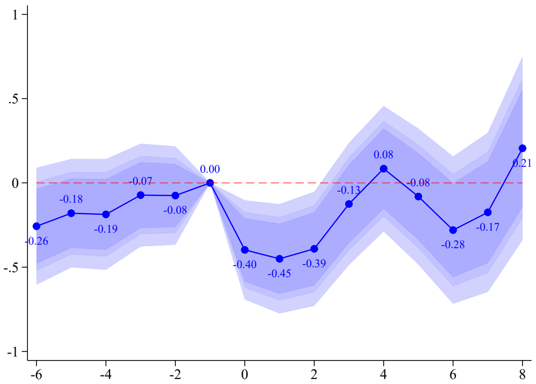
(a) Debt



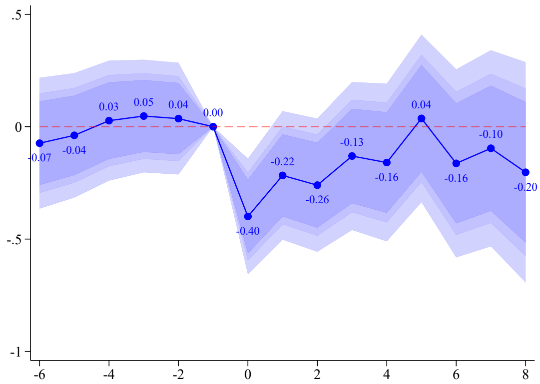
(b) Employment (Social Security sources)



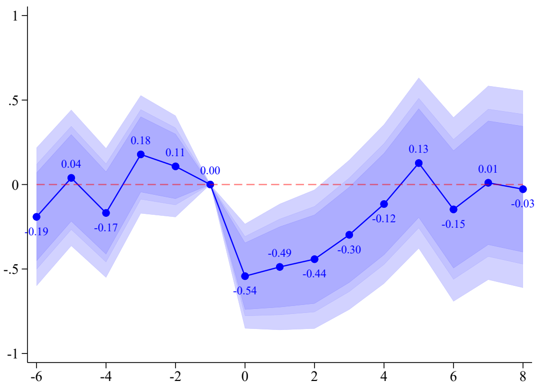
(c) White-collar



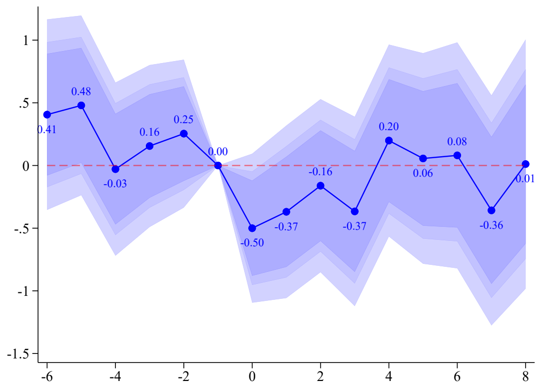
(d) Blue-Collar



(e) Tangible Investment



(f) Intangible Investment



NOTE: This figure presents estimates of the coefficient $\beta_1^h * 100$ associated with demand uncertainty from estimating this equation: $\Delta G_{f,t+h} = \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X_{f,t-1}} + \alpha_2^h D^{M1}_{f,t} + \beta_1^h dD^{M2}_{f,t} + \gamma^h_{k,t} + \gamma^h_f + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the firm-level, are displayed in shades of blue. The size of the shock is set at one standard deviation. E.g.: a one standard deviation uncertainty shock decreases investment growth by 0.45 percentage point the year of the shock.

Table A.0.3: List of Sectors

10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing

References

Aghion, P., A. Bergeaud, M. Lequien, and M. Melitz (2017). The Impact of Exports on Innovation: Theory and Evidence. Technical report, working paper.

Aghion, P., A. Bergeaud, M. Lequien, and M. J. Melitz (2018). The impact of exports on innovation: Theory and evidence. Technical report, National Bureau of Economic Research.

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

Barrero, J. M., N. Bloom, and I. Wright (2017). Short and long run uncertainty. Technical report, National Bureau of Economic Research.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics 98*(1), 85–106.

Berthou, A. and E. Dhyne (2018). Exchange Rate Movements, Firm-Level Exports and Heterogeneity.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics 119*(1), 249–275.

Bloom, N., S. Bond, and J. Van Reenen (2007). Uncertainty and Investment Dynamics. *The review of economic studies 74*(2), 391–415.

Bussiere, M., L. Ferrara, and J. Milovich (2015). Explaining the Recent Slump in Investment: The Role of Expected Demand and Uncertainty. Technical report, Banque de France Working Paper.

Cezar, R., T. Gigout, and F. Tripier (2017). FDI and Uncertainty: Evidence from French Multinational Firms. Technical report, Working Paper.

Chetty, R., A. Looney, and K. Kroft (2009). Salience and taxation: Theory and evidence. *American economic review 99*(4), 1145–77.

Crouzet, N., N. R. Mehrotra, et al. (2017). Small and Large Firms Over the Business Cycle. Technical report.

De Sousa, J., A.-C. Disdier, and C. Gaigné (2016). Export decision under risk.

di Giovanni, J., A. A. Levchenko, and I. Mejean (2017). Large firms and international business cycle comovement. *American Economic Review 107*(5), 598–602.

Esposito, F. (2018). Entrepreneurial Risk and Diversification through Trade.

Favara, G. and J. Imbs (2015). Credit supply and the price of housing. *American Economic Review 105*(3), 958–92.

Gala, V. and B. Julio (2016). Firm Size and Corporate Investment.

Garin, A., F. Silverio, et al. (2017). How Does Firm Performance Affect Wages? Evidence from Idiosyncratic Export Shocks. Technical report, Job Market Papers.

Gaulier, G. and S. Zignago (2010). BACI: international trade database at the product-level (the 1994-2007 version).

Gervais, A. (2018). Uncertainty, risk aversion and international trade. *Journal of International Economics 115*, 145–158.

Gilchrist, S. and C. P. Himmelberg (1995). Evidence on the role of cash flow for investment. *Journal of Monetary Economics 36*(3), 541–572.

Guiso, L. and G. Parigi (1999). Investment and demand uncertainty. *The Quarterly Journal of Economics 114*(1), 185–227.

Hainmueller, J., J. Mummolo, and Y. Xu (2019). How much should we trust estimates from multiplicative interaction models? Simple tools to improve empirical practice. *Political Analysis 27*(2), 163–192.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2017). Firm-level political risk: Measurement and effects. Technical report, National Bureau of Economic Research.

Hummels, D., R. Jørgensen, J. Munch, and C. Xiang (2014). The wage effects of offshoring: Evidence from danish matched worker-firm data. *American Economic Review 104*(6), 1597–1629.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Julio, B. and Y. Yook (2012). Political uncertainty and corporate investment cycles. *The Journal of Finance 67*(1), 45–83.

Khwaja, A. I. and A. Mian (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review 98*(4), 1413–42.

Mayer, T., M. J. Melitz, and G. I. Ottaviano (2016). Product mix and firm productivity responses to trade competition. Technical report, National Bureau of Economic Research.

Vannoorenberghe, G. (2012). Firm-level volatility and exports. *Journal of International Economics 86*(1), 57–67.

Vannoorenberghe, G., Z. Wang, and Z. Yu (2016). Volatility and diversification of exports: Firm-level theory and evidence. *European Economic Review 89*, 216–247.