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The Role of Financial Constraints and Uncertainty

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Abstract

This paper studies the role of capacity utilisation in explaining investment behaviour in Italian SMEs and large firms. We propose a framework in which firms with high capacity utilisation are more likely to invest in maintaining a buffer against future shocks. Using firm-level data from the Bank of Italy's Survey of Industrial and Service Firms (2002–2024), we empirically examine how deviations from a sector-specific target capacity utilisation influence investment decisions, accounting for the roles of uncertainty and financial constraints. Our findings reveal that Italian firms with high growth potential - those at the so-called "growth window" (Coad et al., 2021) - are more likely to invest. This result is primarily driven by large firms, while SMEs do not seem to respond strongly to the presence in such growth windows. Furthermore, we find that uncertainty does not deter investment among firms operating at high capacity, but instead stimulates investment in firms with low capacity utilisation. These insights have significant implications for industrial policy that targets support to firms at critical decision points in their growth trajectory.

Non-Technical Abstract: This paper explores why Italian companies decide to invest and how this depends on their production capacity. We find that firms running near full capacity are more likely to invest, especially larger companies. Surprisingly, uncertainty in the economy does not deter high-capacity firms from investing; instead, it can even encourage investment among companies which utilise less of their capacity. Our results suggest that supporting firms at key points in their growth could help boost investment and strengthen the Italian economy.

***Keywords*:** Capacity Utilisation, Investment, Uncertainty, Financial Constraints, Firm Growth
JEL Codes: D20, D22, D24, D81, E32, L11

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1 Introduction

Over the past few decades, the Italian economy has grappled with frequent and substantial shocks, with persistent effects. Italy not only suffered during the Great Recession of 2008-2009 (Zamagni, 2018) but also struggled to manage the fallout from the European debt crisis (Bull, 2020) and experienced frequent changes in government between 2011 and 2021 (Balduzzi et al., 2020), followed by the pandemic shock. These shocks have affected various aspects of the economy, such as investment (Bond, Rodano and Serrano-Velarde, 2015; Busetti, Giordano and Zevi, 2015), productivity (Bugamelli et al., 2018), and the labour share (Bloise, Brunetti and Cirillo, 2021), further hampered by misallocation of resources and low market dynamism (Calligaris et al., 2018; Cucculelli and Peruzzi, 2020), and fiscal policy uncertainty (Anzuini, Rossi and Tommasino, 2020). These developments have led to a lack of overall productivity growth (Dosi et al., 2012; Zeli, Bini and Nascia, 2022; Fernald and Inklaar, 2020), which has hindered the potential for economic growth over the last few decades (Bugamelli et al., 2018). The economic literature has overlooked the potential role of a structural and persistent drop in Italian manufacturing firms' capacity utilisation in explaining these episodes of poor economic performance.

According to Nelson (1989), capacity utilisation is "*the ratio of actual to the maximum potential output consistent with a given capital stock*". Once a firm (or an economy) operates at a high capacity utilisation rate, it requires more investments to maintain its efficacy and achieve growth (Axsäter and Olhager, 1985; Artica, 2023). On the other hand, lower capacity utilisation is associated with higher average costs and lower productivity growth (Hulten, 1986; Butters, 2020; Ray, Walden and Chen, 2021). This measure has been repeatedly used as an indicator of macroeconomic cycles and productivity in the economic literature (Krugman, 1994; Pozzi and Schivardi, 2016; Cette et al., 2015; Butters, 2020), especially in the manufacturing sector (Corrado and Mattey, 1997). At the country level, we document a tight association between average capacity utilisation and aggregate investments (represented by Gross Fixed Capital Formation or GFCF) of selected European economies in Figure A.1 of Appendix B.1.[1]

As discussed above, the Italian economy has experienced low levels of capacity utilisation and aggregate investments. Figure 1 below provides a more detailed context, where the quarterly correlation between aggregate investments and capacity utilisation is positive, with a magnitude of 0.38. Capacity utilisation is more strongly pro-cyclical than aggregate investments, measured by their correlation with the recession dummy defined as OECD recession bands (-0.32 vs -0.10).

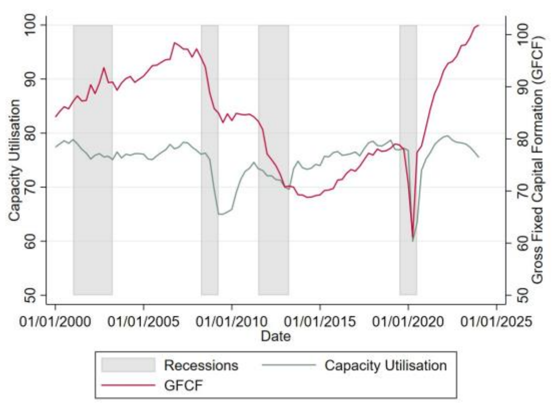


Figure 1: Capacity utilisation vs aggregate investments in Italy. Data source: Business Tendency Survey, OECD (2024)

Since the Great Recession and the European debt crisis, Italian firms have displayed a structurally lower capacity utilisation and low investments and have faced tight financial constraints (Minetti and Zhu, 2011) and

[1]The capacity utilisation of Italian manufacturing firms has remained one of the lowest among European economies (see the left panel of Figure A.1 of Appendix B.1).

high uncertainty (Bontempi, Golinelli and Parigi, 2010; Gufler et al., 2020). These constraints appear to be particularly binding for Small and Medium Enterprises (SMEs): the funds raised by Italian SMEs were allocated mainly to capital restructuring rather than growth-oriented investments (Fasano et al., 2025). Furthermore, the propensity to borrow by smaller Italian firms is typically lower, regardless of constraints (Guiso, 2003). Lastly, the previous literature has shown that growing SMEs may face higher credit prices, which in turn reduces the chance that these firms capitalise on their growth window (Rostamkalaei and Freel, 2016). In this environment, Busetti, Giordano and Zevi (2015) argued that low capacity utilisation may be a driver of manufacturing firms' poor outcomes.

Firms' investment decisions are primarily determined by the business cycle (Gourio and Kashyap, 2007; Doms and Dunne, 1998) and Tobin's q, which signals expected returns from investments (Blundell et al., 1992). Real options theory has become a central explanation for why investments decline during highly uncertain episodes of the business cycle (Dixit and Pindyck, 1994; Bloom, Bond and Van Reenen, 2007). This theory posits that uncertainty over future demand reduces firms' ongoing investment due to higher real options and capital irreversibility, thereby increasing the value of waiting and delaying investments.[2] Enriching the real options model by considering the role of capacity utilisation, Abel et al. (1996) set up a model where capital investment decisions are limited by firms' ability to sell later or expand their capacity: the option to expand reduces the incentive to invest, contrary to the option to disinvest. In addition, firms' investments rely on external financing via borrowing (Fazzari and Petersen, 1988; Amiti and Weinstein, 2018), which can be scarce during turbulent times for reasons such as tight credit supply, lower credit ratings and asymmetric information on firms' performance. Moreover, the firm's growth and expansion process is not the result of smooth investments over time, but rather a few extensive and costly investment events, investing a lumpy process featuring bumps and jumps (Doms and Dunne, 1998; Arata, 2019).[3] Plant-level data have previously shown that investment spikes (the "extensive margin") account for the majority of variation in aggregate investment statistics (Gourio and Kashyap, 2007). Periods of inaction followed by bursts of investments are a pervasive manifestation of capital adjustment frictions (Baley and Blanco, 2021). Therefore, the spiky nature of expansion investments further extends the dependence of investment decisions on external financing conditions (Im, Mayer and Sussman, 2020) and increases capital adjustment costs, as firms' internal funds are insufficient to finance these large investment spikes. Unlike expansion investments, smooth investment rises and falls are usually due to the maintenance of capital. Throughout our analysis, we will isolate large investments to represent expansion investments better.

Previous studies have demonstrated that predictions of firms' investment based on the business cycle and Tobin's q are subject to bias if the firms' capacity utilisation is not accounted for (Grullon and Ikenberry, 2025), since a secular erosion in capacity utilisation may offset the effect of increasing average q's. Through the span of capacity utilisation values, a trigger point (or capacity target) exists that stimulates firms' decisions to invest (Brown and Mawson, 2013), especially when faced with unanticipated demand shocks (Abel, 1981). Firms choose their technology-dependent long-run capacity utilisation targets endogenously, which are lower during recessions (Nikiforos, 2011). A firm that operates above its desired capacity utilisation is known to be at the *growth window* [4] and is more likely to invest, expand, and achieve growth (Coad and Planck, 2012). Nevertheless, some firms at the growth window will not invest and instead stall or shrink due to low growth desires or external factors (Loderer, Stulz and Waelchli, 2017; Boot and Vladimirov, 2019). Thus, firms at the growth window can follow different paths, or in other words, they have reached a "fork in the road" (Coad et al., 2021). This theory, along with the associated empirical results, suggests that a trigger point of capacity utilisation exists, through which firms decide upon their future and either invest, pause, delay, or shrink (Coad and Srhoj, 2020). We

[2]However, some studies find that such results do not hold in competitive markets even in the presence of irreversibility (Abel and Eberly, 1994). Furthermore, Pozzi and Schivardi (2016) shows that firms only partially respond to shocks due to adjustment frictions.

[3]In other words, investment is not buying a square meter of land per day, but buying a large area at one time (Penrose and Pitelis, 2009).

[4]Firms close to their capacity target will see themselves at the window of opportunity for high growth in the next period. The importance of such windows in innovation, technology adoption, policy and industrial organisation has been studied previously; for instance, see Lee and Malerba (2017); Giachetti and Marchi (2017). We focus on the behaviour of these firms since they are the main drivers of aggregate investments and economic growth (Asturias et al., 2023).

extend this framework by considering how the execution of the planned investment depends upon factors such as the prevailing uncertain macroeconomic landscape (Saltari and Travaglini, 2001; Bolton, Wang and Yang, 2019) and the availability of financial resources.

In summary, our research presents a framework for studying the interplay between firms' investments, capacity utilisation, uncertainty, and financial constraints. We aim to answer two main research questions: 1) Does a firm's probability of investing depend on capacity utilisation, and does it depend on whether it has entered its growth window? How does firm size moderate these effects? 2) How do financial constraints and aggregate uncertainty influence the relationship between capacity utilisation and investment? Is there heterogeneity between firms at and outside of the growth window concerning the role of these two factors?

This paper's findings align with the previous literature, stating that firms with high capacity utilisation and in the growth window have more investment incentives than those with lower capacity utilisation. Even though we find that firms operating at high capacity are not sensitive to uncertainty regarding their investment decisions, the investments of those operating at low capacity are positively affected by uncertainty. Therefore, not only do our results highlight the significance of uncertainty and financial constraints for Italian firms at the growth window, but they also underscore the heterogeneity of the impact of uncertainty on firms' investments, similar to Howes (2023). Firms' size, as measured by the number of employees, can to some degree determine the reaction of the firm to presence at the growth window as smaller firms do not show tendency to invest when a growth opportunity is available. Furthermore, size plays an important role in heterogeneous response to uncertainty. While larger firms' investments remain unaffected by swings in uncertainty, medium and small firms tend to increase their investments during uncertain times. This may be because SMEs rely on their entrepreneurial strategic posture to compete in the industry, which gives them an edge when the economy is more volatile (Cowden et al., 2022). This insight helps us expand the literature on Italian firms' inefficiencies[5], building on Secchi, Tamagni and Tomasi (2016); Schivardi, Sette and Tabellini (2022); Calligaris et al. (2018).

However, the influence of capacity utilisation in our sample of Italian manufacturing firms may be weaker than that observed in other studies. The ownership and governance structures of large Italian companies are often characterised by concentrated family management, which may prioritise maintaining control over the business at the expense of potential growth opportunities (Grazzi and Moschella, 2018; Davidsson, 1989).

This paper is structured as follows. In Section 2, we outline our conceptual framework. The empirical strategy is detailed in Section 3. Section 4 presents the Survey of Industrial and Service Firms database and discusses the properties of the variables employed in our empirical analysis. Following that, Section 5 presents the results of our empirical analysis, subject to various robustness checks outlined in Section 6. Finally, Section 7 concludes our paper.

2 Conceptual Framework

This section presents a conceptual framework illustrating how changes in a firm's realised capacity utilisation impact its investment decisions, building on the "fork in the road" framework introduced by (Coad et al., 2021).[6] Using this framework, we highlight the role of uncertainty and financial constraints in shaping these decisions.

2.1 Investment & Capacity Utilisation

Information on capacity utilisation plays a crucial role in guiding firms' investment decisions. Firms use a long-term utilisation target for their production capacity (Di Domenico, 2023), which we define as $CU^{\psi} \in [0, 100]$ and they try not to deviate too much from it to avoid inventory costs (Abel, 1981; Sarkar, 2009). This target integrates a precautionary capacity buffer to respond to demand surges (Greenwood, Hercowitz and Huffman, 1988; Fagnart, Licandro and Portier, 1999) or to deal with maintenance needs (Dagdeviren, 2016). A firm operates in the "growth window" when observed utilisation meets or exceeds the target ($CU \geq CU^{\psi}$, i.e. they

[5]Investing during highly uncertain times is inefficient as the outcome is less predictable and reduces firms' resources in facing later shocks.

[6]This model is then tested for firms represented in EIBIS and ORBIS in Europe.

operate at overcapacity $O = 1$). At this growth window, firms may either invest to return to the long-term capacity target, or delay expansion, e.g due to financial constraints or unfavourable external conditions, which is why Coad et al. (2021) refer to it as "fork in the road". In addition, firms' investments may also depend on how distant the firm is from its target, namely the gap ($CU - CU^{\psi}$). As displayed in Figure 2, once a firm enters the growth window at time τ, it can either reduce its capacity utilisation by investing in new production capacity (dashed green path), or delay investment, leading to a high or even higher capacity utilisation rate (dashed red path).

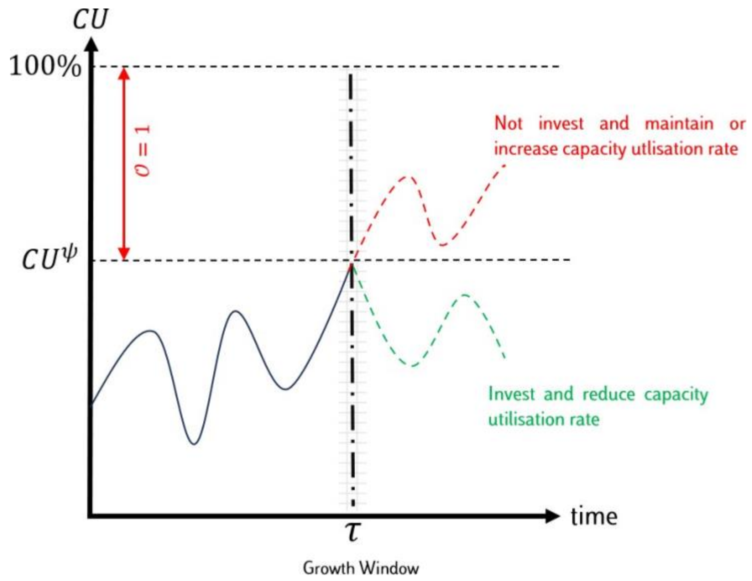


Figure 2: Firms' decision at the growth window, inspired by Coad et al. (2021)

Below we elaborate on how we incorporate the role of financial constraints and uncertainty in this framework.

2.2 The Role of Uncertainty and Financial Constraints

Our analytical framework has thus far operated under the simplifying assumption that firms can fully realise their desired investment levels without encountering financial constraints, while also overlooking the impact of uncertainty. As explored in more detail in Section 1, firms facing elevated levels of uncertainty tend to adopt a more cautious investment approach. This caution arises because uncertainty increases the perceived risks associated with capital expenditures, prompting firms to delay or scale back investment decisions. Moreover, firms grappling with financial constraints, such as limited access to credit or insufficient internal cash flows, often struggle to fully fund their desired investment projects, even when growth opportunities are present. In contrast, when a firm experiences low levels of uncertainty, it is more likely to pursue investments aimed at expanding its production capacity, provided that financial constraints do not impede the realisation of these investment decisions. This interplay between uncertainty and financial limitations significantly shapes a firm's strategic choices and overall economic behaviour.

3 Empirical Approach

In this section, we explain our empirical approach for testing the implications of the conceptual framework presented in Section 2. We test whether the positive distance of capacity utilisation to target ($CU - CU^{\psi}$) and being at the growth window ($CU > CU^{\psi}$) affect firms' investments, represented by investment rates ($I_{i,t}/\bar{Y}_{i,t-1}$), and for investment spikes ($S_{i,t}$). In what follows, we will focus on the capacity utilisation gap (CU - $CU^{\psi}_{s,\tau}$) and whether firms have surpassed their target and are at the growth window. We also assume this target is constant within each sector (s) and depends on the economy's state (τ).

Our econometric framework captures the dynamics between firms' investment and the gap between firms' capacity utilisation and a sector-specific target as follows:

$$y_{i,t} = \begin{cases} I_{i,t}/\bar{Y}_{i,t-1} \\ \mathcal{S}_{i,t} = \rho\left(CU_{i,t} - CU^{\psi}_{s,\tau}\right) + X_{i,t}\beta + \mu_i + \gamma_t + \varepsilon_t \end{cases}$$

The dependent variable $y_{i,t}$ represents firms' investment, measured in two ways. First, we consider the investment rate (investment normalised by sales)[7] and in a different specification, we focus on large investment events, the investment spikes.[8] The vector $X_{i,t}$ contains firm-level controls, and μ_i and γ_t represent firm and time-fixed effects, respectively, to control for the impact of time-invariant firm characteristics and business cycles.

As discussed in Section 2, firms that operate above the target are in the growth window. Therefore, their decisions differ from those of all the other firms as they are expected to benefit more from investing. To capture this non-linearity in the gap to capacity target ($CU_{i,t} - CU^{\psi}_{s,\tau}$), we test our framework with the overcapacity (growth window) dummy, defined as $O_{i,t} = 1$ if $CU_{i,t} > CU^{\psi}{}_{s,\tau}$

As explained in more detail in Section 2, uncertainty and financial constraints hinder firms' external financing of investments. Our econometric framework, considering their role, takes the form of:

$$y_{i,t} = \begin{cases} I_{i,t}/\bar{Y}_{i,t-1} \\ \mathcal{S}_{i,t} \\ \quad = \alpha_1\left(CU_{i,t} - CU^{\psi}_{s,\tau}\right) + \alpha_2 FC_{i,t} + \alpha_3 U_{i,t} \\ \quad +\alpha_4 FC_{i,t} \times U_{i,t} + \alpha_5 FC_{i,t} \times \left(CU_{i,t} - CU^{\psi}_{s,\tau}\right) \\ \quad +\alpha_6 U_{i,t} \times \left(CU_{i,t} - CU^{\psi}_{s,\tau}\right) \\ \quad +X_{i,t}\beta + \mu_i + \gamma_t + \varepsilon_{i,t} \end{cases}$$

In Equation 2, $U_{i,t}$ represents uncertainty faced by firm i at time t, and $FC_{i,t}$ is a dummy for financially constrained firm-year observations. This equation, therefore, estimates not only the impact of the gap-to-capacity target in determining investment rates (spikes) but also measures the role of financial constraints, uncertainty, and their interactions with each other, as well as the capacity utilisation gap to the target. Similar to Equation 1, we also test this framework for $O_{i,t}$.

We are aware of the endogeneity concerns that might arise due to simultaneity (Almeida and Campello, 2001), omitted variable bias (Alti and Tetlock, 2014), and measurement errors, as we do not have comprehensive information on firms' financial data. The sample selection bias can also influence the relationship between financial constraints and investments, as our sample primarily consists of large firms. Reverse causality can also occur when financial constraints and investments mutually affect each other, complicating the determination of causality. For instance, firms that invest more intensively over time may be less financially constrained due to higher credit ratings or better bank relationships.

To address these issues, we will employ an instrumental variable approach to study the role of financial constraints, thereby mitigating endogeneity and simultaneity. We follow Alfaro, Bloom and Lin (2024), who used a 5-year lagged dummy to capture ex-ante financially constrained firms.[9] In our work, we do not rely on indirect proxies for financial constraints and use firms' direct responses to the questions regarding their financial constraints. Therefore, one lag is sufficient and provides us with a larger number of observations in the estimation. Given our access to firms' explicit answers to whether they are financially constrained in the Survey of Industrial and Service Firms, we modify their method by reducing the number of lags to one. Our instrument is well-relevant as many firms remain financially constrained for consecutive years, and the constraints in the

[7]Normalising investments by capital is a more conventional approach. However, we do not have access to data on capital (e.g. total assets).

[8]Investment spikes attempt to isolate large (expansion) investments from the normal wear and tear capital replacements. For a comprehensive review, please refer to Arata (2019); Bachmann, Elstner and Hristov (2017).

[9]Their method uses a proxy based on financial data and Moody's aggregate index.

past cannot theoretically explain the probability of delay or large investments in the present or future.

In our two-stage control function regression following Angrist and Pischke (2009), the first stage predicts the probability of remaining financially constrained for the previously constrained firms:

$$Pr(FC_{i,t} = 1) = \lambda FC_{i,t-1} + \mu_i + \gamma_t + u_{i,t}$$

The results of this regression are provided in Appendix B.7. This equation captures the probability that a firm remains consecutively financially constrained (over two periods), considering the business cycle and firms' unobserved characteristics, which are captured by time (γ_t) and firm (μ_i) fixed effects, respectively.

We then plug the predicted probability from the first stage Equation 3 as ($\widehat{FC}_{i,t} \equiv E_t\left[Pr(FC_{i,t} = 1)\right] = \lambda FC_{i,t-1}$) into Equation 2 and replace the financial constraint dummy with the predicted probability. We then proceed by estimating the new equation below:

$$\begin{aligned} y_{i,t} = \begin{cases} I_{i,t}/\bar{Y}_{i,t-1} \\ S_{i,t} \end{cases} &= \alpha_1\left(CU_{i,t} - CU^{\psi}_{s,\tau}\right) + \alpha_2\widehat{FC_{i,t}} + \alpha_3 U_{i,t} \\ &+\alpha_4\widehat{FC_{i,t}} \times U_{i,t} + \alpha_5\widehat{FC_{i,t}} \times \left(CU_{i,t} - CU^{\psi}_{s,\tau}\right) \\ &+\alpha_6 U_{i,t} \times \left(CU_{i,t} - CU^{\psi}_{s,\tau}\right) \\ &+X_{i,t}\beta + \mu_i + \gamma_t + \varepsilon_{i,t} \end{aligned}$$

This equation isolates the roles of capacity utilisation, financial constraints, and uncertainty, as well as their interaction with our outcome variables of interest, without the endogeneity issues previously discussed. constraints to uncertainty and investments.

We now proceed by elaborating on the estimation methods which will be applied to the regression equations shown so far.

3.1 Estimation Methods

Throughout this paper, we employ two econometric methods for estimating Equations 1, 2, 3, and 4. We apply a standard panel OLS approach when the dependent variable is the investment rate. Instead, for regressions with binary outcomes, those involving investment spikes ($S_{i,t}$) and financial constraints ($FC_{i,t}$), we use the conditional logit (CLogit) method. This method is particularly suitable for modelling binary outcomes in matched or highly stratified datasets (Hosmer Jr, Lemeshow and Sturdivant, 2013) and for panel data, as it allows for the inclusion of fixed effects, thereby controlling for unobserved characteristics (Kwak, Martin and Wooldridge, 2023).

In conditional logit models, parameter estimation is based on variation within each group. If a panel unit, such as an individual or firm, consistently exhibits the same outcome across all observations (i.e., all outcomes are either 0 or 1), the model cannot establish comparisons within that group, rendering it uninformative for parameter estimation. Therefore, the model will exclude firms that do not experience an investment spike from the regression. A detailed explanation of our estimation is available in Appendix A.

This section introduced the empirical approach used in this paper as the econometric counterpart of the conceptual framework discussed in Section 2. We now examine the data used in our study and the variables that comprise this empirical framework.

4 Data and Variables

4.1 Dataset

In this work, we use the 2002-2024 panel of the Survey of Industrial and Service Firms (Bank of Italy, 2024)[10] firm-level dataset. This survey is administered annually to approximately 4,000 Italian firms with at least 20 employees in the manufacturing and services sectors. The Bank of Italy has continuously collected information on firms' key characteristics such as employment, investment (actual and planned), turnover, debt and trade receivables. The Survey of Industrial and Service Firms includes questions on firms' actual and expected capacity utilisation. Additionally, since the Great Recession of 2007-08, the Survey of Industrial and Service Firms includes questions on firms' financing and relevant conditions and constraints. However, this dataset does not contain information on all of the firms' balance sheet items and plant-level production processes. Finally, the survey also collects information on periodically changing topics of particular interest to economic research (e.g., corporate strategies and governance, physical, human, and organisational capital, and electric power).

The Survey of Industrial and Service Firms's coverage increased after 2002, as it was introduced to more manufacturing and non-financial private service firms with 20 or more employees, excluding credit institutions, insurance companies, public services, and other social and personal services. As a result, participating firms have increased to more than 4,000 (3,000 in the manufacturing sector and 1,000 in services). In what follows, our analysis will be limited to post-2002 survey waves to avoid potential mismeasurements. Furthermore, we focus on the manufacturing sector, which constitutes 72% of all observations and 52% of employment in the entire sample, and is shown to be more sensitive to capacity utilisation dynamics (Berndt and Fuss, 1982; Koenig, 1994). Out of 94,330 observations from 2002 to 2024, covering 12,094 unique firms, 67,662 observations correspond to 8,502 unique firms in the manufacturing sector. Lastly, the variable that defines the most granular sectors in the economy available to us is based on the aggregation of ISTAT ATECO 2002 and ISTAT ATECO 2007 from the Italian Statistical Office (ISTAT), and divides the manufacturing firms into 7 sectors. Table A.1 in Appendix B provides a detailed list of this aggregation and the resulting sectors for use.

We now demonstrate the variables we use from the Survey of Industrial and Service Firms to construct measures corresponding to the empirical analysis.

4.2 Variables

This section presents a detailed discussion of our variables and then discusses how these steps help frame our econometric model as described in Section 3. We develop various metrics for investment, uncertainty, employee and sales growth and reliable controls. The questions from the Survey of Industrial and Service Firms used in our analysis are presented in Appendix C.

Measuring Investment The Survey of Industrial and Service Firms includes questions on both realised investments each year (t) and the expected investments in the next year ($t + 1$) in nominal euros, which are then converted to real values using deflators. As a firm's size typically influences investment values, the variable should be normalised using an appropriate proxy for this factor. The literature has used various forms of investment rate to tackle this issue (Belo, Lin and Bazdresch, 2014; Grazzi, Jacoby and Treibich, 2016; Alfaro, Bloom and

[10]This survey has been collected under different names since 1984. The current name is INVIND or "Indagine sugli investimenti delle imprese manifatturiere" (Inquiry into investments of manufacturing firms). The high-quality data collection and supervision have attracted many researchers to use this data to analyse various economic topics, such as investment (Bond, Rodano and Serrano-Velarde, 2015), capacity utilisation (Locatelli, Monteforte and Zevi, 2016), productivity and firm growth (Pozzi and Schivardi, 2016), and labour outcomes (Daruich, Di Addario and Saggio, 2023). The dataset is accessible through an online platform (RemoteExecution - REX) of code execution (using R and STATA). The output can only include text (.txt format). This shortcoming means that we cannot investigate the distributional properties of variables, such as their histograms or Kernel densities. Furthermore, direct access to view the data and single observations is limited for confidentiality reasons. Hence, we cannot observe the percentiles of the variables or their minimum and maximum values. The use of the dataset is discussed in more detail by Bruno, D'Aurizio and Tartaglia-Polcini (2014).

Lin, 2024)[11], which commonly take the shape of $\frac{I_t}{K_{t-1}}$ or $\frac{I_t}{0.5(K_t+K_{t-1})}$, where I_t is the flow and K_t is the stock of capital. Our dataset does not include information on firms' capital stock. Therefore, we rely on intuitions from Baum, Caglayan and Talavera (2008) and use the average recent sales ($\bar{Y}_{i,t-1} = 0.5\,[Y_{i,t} + Y_{i,t-1}]$) instead of capital to normalise investments. In our case, the use of average recent values is motivated by the volatility of annual sales. Ultimately, to ease our notation, we show our investment rate as $I_{i,t}/\bar{Y}_{i,t-1}$ and calculate it as:

$$I_{i,t}/\bar{Y}_{i,t-1} = \frac{I_{i,t}}{0.5(Y_{i,t} + Y_{i,t-1})} \tag{5}$$

Using the same methodology, we also calculate the expected investment rates by replacing the investment values at t with expected values for $t + 1$ reported by the firms. This additional step will help us in the later stages of our analysis, where we attempt to find the spikes in the investment process.[12]

The above-mentioned investment rate does not distinguish between expansion and replacement (or maintenance) investments. The literature has previously discussed the notion that investment is discrete, with firms deciding to invest in some years and only perform minimal maintenance in others (Arata, 2019). In other words, most of the observed investments in plants and machinery are for replacement, maintenance or depreciation (Mobley, 2011). Thus, to analyse firms' investment decisions, we must isolate the investment spikes from other less meaningful periods and consider the lumpiness of investments. Ideally, a spike definition must satisfy two properties in addition to being rare across and within firms: 1) it should display a sudden jump in investment rates, and 2) it must be unexpected to the firm in the previous period (Grazzi, Jacoby and Treibich, 2016; Bachmann, Elstner and Hristov, 2017).

To understand at what point in the investment distribution the spikes occur, we need to observe the ordered distribution (based on percentiles) of the realised and expected investment rates. In the distribution of realised investment rates, the kink point determines the first property for an investment spike, indicating a sudden jump. In contrast, a post-kink large positive distance between the ordered distribution of realised and expected investment rates displays the second property of an investment spike, namely that it is unexpected to the firm. However, we cannot observe this ordered distribution and relevant percentiles for confidentiality reasons, as they grant access to single observations. Therefore, we construct a proxy for these percentiles as follows. We start by identifying the investment rate percentiles for each year and storing them in the background, without directly observing these values. We then calculate the average investment rate at percentiles, namely, calculating the average value for each percentile observed over the years. Using formal notations, we can write:

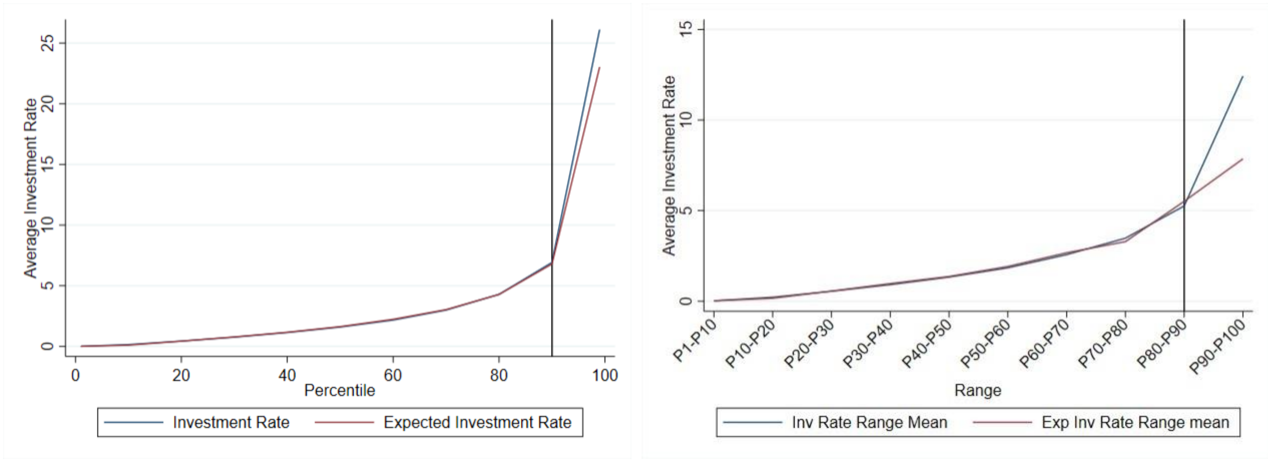
$$\text{Average Annual Realised Investment Rate at Percentile } p \equiv \bar{P}^{I}(p) = \frac{1}{T}\sum_{t=1}^{T} P_t^{I}(p)$$

$$\text{Average Annual Expected Investment Rate at Percentile } p \equiv \bar{P}^{I,e}(p) = \frac{1}{T}\sum_{t=1}^{T} P_t^{I,e}(p)$$

Where T is the total number of years, $\bar{P}$ is the resulting value that we can observe, and P represents the percentiles that result directly from inquiry into data and we cannot observe. Concerned about the possibility that single observations drive these averages at the tail of the percentiles, we also calculate the range average among observations between the percentiles of interest. These results are presented below:

[11] Furthermore, normalisation is carried out to reduce the skewness and smooth out any other non-normal characteristics.

[12] The availability of expected values allows us to consider the role of a spike in planned investment rates and check whether it only occurs for planned investments or happens to the expected investments. Furthermore, it enables us to understand the changes in the dynamics of the ranked distribution before and after the spike, as well as how observed investments differ from the expected values after the spike.



(a) Percentile Mean

(b) Range Mean

Figure 3: Average (Expected) Investment Rates

We observe two phenomena. Primarily, and in Figure 3(a), we observe a sudden jump in investment rates above the 90th percentile, before which the growth is very smooth. This result is confirmed in Figure 3(b), where the spike is still present even though the jump is smoother by the intra-decile mean's construction. Hence, we can confirm the first criterion: a sudden jump exists at around the 90th percentile. Furthermore, we document another development after the 90th percentile: the distance between the blue (realised investment rates) and red (expected investment rates) expands significantly. This feature demonstrates the second important characteristic of a true spike, being unexpected to the firm in the period preceding the investment planning. The spike observations are assigned by setting the dummy $S = 1$ for the investments at and beyond the 90th percentile of the investment rates across the whole sample. Our analysis reveals that spikes are rare, and only a few firms experience spikes in each period. Indeed, only 916 out of 3,666 firms (25%) in our analysis have experienced an investment spike at least once, which is in line with intuitions from Grazzi, Jacoby and Treibich (2016) that only a few firms observe spikes, especially in economies with tight borrowing conditions.

Capacity utilisation gap and overcapacity variables We are interested in studying the role of the deviation of the observed capacity utilisation from the capacity target ($CU_{i,t} - CU^{\psi}_{s,\tau}$) as a determinant of firms' investments. First, we need to define the target ($CU^{\psi}_{s,\tau}$) within each sector s[13] as also discussed in Nikiforos (2013) and motivated by minimising costs due to returns to scale. Furthermore, these targets may differ depending on the state of the economy (τ) (Shapiro, Gordon and Summers, 1989; Dotsey and Stark, 2005) as shown by the strong cyclicity of capacity utilisation in Figures A.1 & 1. During expansions - especially at the beginning - the average capacity utilisation across firms surges as firms use their resources to cope with the demand pressures. Differently, firms adjust their utilisation rate towards lower values during recessions to avoid the adjustment costs associated with inputs. Therefore, there is a structural difference between expansion and recession periods. Aware of this issue, in our work, we use a sector-wide average of capacity utilisation in recessionary and non-recessionary periods and assign it to the firms in that sector as a capacity utilisation target. Ultimately, those firm/year observations with a higher capacity utilisation than the target will be assigned the dummy $O_{i,t} = 1$ and will be interchangeably referred to as "operating at capacity" or "in growth window." This dummy helps us isolate the non-linear effect of capacity utilisation on firms' investments.

Financial constraints Next, we categorise observations into those with and those without financial constraints. We use a set of questions[14] in the Survey of Industrial and Service Firms implemented after 2008 to identify the firms that failed to receive loans (and funds) or chose not to apply to external funding, since they

[13]We assume that the ISTAT sectors in our dataset have different technology and production processes from each other. Furthermore, a sector-wide approach allows firms with few observations, who have not responded to the survey frequently, to have a reasonable target.

[14]The questions used are available in Appendix C

were sure they would not obtain them. We first use the question of whether firms desire to increase their debts. They were not financially constrained if they had no desire to increase their debt (FC = 0). Among those who desired to increase their debt, some have obtained their desired funds. We assign these observations as non-constrained (FC = 0). Those firms that either did not (or partially) receive their funds or did not apply because they were sure they would not obtain the funds are assigned as constrained (FC = 1).

Uncertainty measure To compute uncertainty, we use overall uncertainty developed by Mohades, Piccillo and Treibich (2024), computed as the cross-sectional dispersion of the residuals of an AR(1) process on sales. This method calculates firms' overall uncertainty first by running the following AR(1) of sales to isolate the unpredictable component in the residual:

$$\log(Y_{i,t}) = \omega \log(Y_{i,t-1}) + \varepsilon_{i,t} \tag{6}$$

In the second step, it calculates the residual average at each firm ($\bar{\varepsilon}_i$) to measure the cross-sectional dispersion of these anomalies as:

$$U_{i,t} = (\varepsilon_{i,t} - \bar{\varepsilon}_i)^2 \tag{7}$$

This uncertainty measure captures the unpredictable component of a simple AR(1) process, specifically its volatility. However, the observed volatility of sales is endogenous to diversification opportunities of firms, as entrepreneurs can endogenously reduce risk by choosing safer, more conservative investments and products (Michelacci and Schivardi, 2013). To address endogeneity, we modify our measure of uncertainty by computing a sector-averaged uncertainty, or formally within each sector $s \in S$ with N_s firms at time t as:

$$U_{s,t} = \frac{\sum_{i=1}^{N_s} U_{i,t}}{N_{s,t}} \text{ For } s = 1, \ldots, S$$

The sectoral uncertainty is then normalised to a value ranging from 0 (no uncertainty) to 100 (extreme uncertainty).

Control variables The literature on the determinants of investment indicates that firms' size, growth, cash flows, and profits are relevant factors in determining such decisions (Nguyen and Dong, 2013; Bokpin and Onumah, 2009). Furthermore, firms choose strategic timing in their investments and hiring, as these two complement each other in production. The profits from the past period can be used as liquid resources for ongoing investments through internal funding. Therefore, we use firms' growth (growth in the number of employees, lagged one year, denoted as $L^G_{i,t-1}$) and profitability (lagged one year, denoted as $\pi_{i,t-1}$) as a measure of past performance as control variables. The information about firms' profitability in the Survey of Industrial and Service Firms consists of a five-category variable on the degree of profitability (or losses). This categorical variable consists of whether the firm is experiencing large losses, some losses, no losses, some profits, or large profits. From this variable, we construct a profitability dummy (π) that equals 1 when the firm is profitable and 0 otherwise.

Lastly, uncertainty is a pervasive phenomenon. It persists within firms over time and impacts the decision for more than one period. Our measures of uncertainty also conform to this behaviour, as shown by the high autocorrelation coefficients in Appendix B.6. Hence, our analysis also controls for lagged uncertainty ($U_{s,t-1}$).

4.3 Descriptive Statistics

Below, we provide the descriptive statistics of the variables used in our analysis:

Variable		Mean	Std Dev	Observations
Raw Variables				
$Y_{i,t}$	Sales	238,142.40	3,212,467	67,662
$I_{i,t}$	Investments in Plant and Machinery	8,292.25	75,726.01	40,590
$L_{i,t}$	Nb. of Employees	261.41	1,111.47	67,662
Constructed Variables				
$I_{i,t}/\overline{Y}_{i,t-1}$	Investment Rate	3.87	45.10	40,587
$S_{i,t}$	Spike	0.10	0.30	40,587
$CU_{i,t}$	Capacity Utilisation	76.56	15.09	55,002
$CU_{i,t} - CU^{\psi}_{s,\tau}$	Gap to target capacity	0.00	15.03	55,002
$O_{i,t}$	Overcapacity dummy	0.55	0.50	55,002
$U_{s,t}$	Sectoral Uncertainty	4.60	5.97	64,607
$FC_{i,t}$	Financial Constraint dummy	0.06	0.24	43,380
$\pi_{i,t-1}$	Lagged Profitability dummy	0.70	0.46	49,976
$L^{G}_{i,t-1}$	Lagged Employment Growth rate	0.01	0.11	43,676

Table 1: Data Description Table

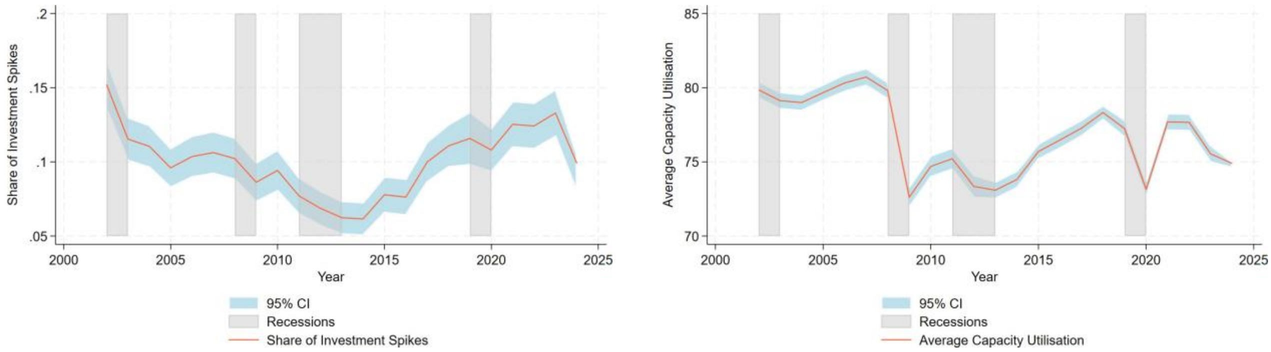
Table 1 provides information on our variables' distributions' first and second moments. Our raw variables indicate that, although small and medium-sized firms are not included in this survey, there is significant variability across our sample. Additionally, more than half of the observations in our sample operate in the growth window. More than two-thirds of the observations in our sample showed profitability in the last period, while the annual employee growth rate averaged 1%. We also provide the descriptive statistics for firms at and outside the growth window in Table A.3 of Appendix B.4. Based on t-tests, firms at the growth window, on average, display higher sales and investments, are larger, have higher capacity utilisation, and face fewer financial constraints and more demand uncertainties. Furthermore, they are more profitable and more likely to have displayed growth.

As our further analysis suggests, there is significant heterogeneity among firm types based on size distribution. In Appendix B.5, we demonstrate that larger firms are more likely to experience overcapacity status as their capacity utilisation is, on average, higher. Furthermore, a higher investment rate among larger firms demonstrates how firm size can influence firms' tendencies for investment and risk-taking.

We also provide a correlation matrix of these variables in Appendix B.3. We observe that firms operating at higher capacity exhibit higher investment spikes but lower investment rates, indicating that they have lower maintenance investments (as reflected in lower investment rates) and larger expansion investments (as evidenced by more spikes). Furthermore, we can see that financial constraints occur more frequently for firms outside the growth window, but they contract investments across the entire sample. Uncertainty for firms at the growth window is lower and is positively correlated to financial constraints, as demonstrated in more detail by Alfaro, Bloom and Lin (2024); Huynh (2024). Firms at the growth window have higher chances of profitability, which is positively correlated to expansion investments (spikes). Lastly, employee growth positively correlates to capacity utilisation, investments and profits.

4.4 Investment, Capacity Utilisation and the Business Cycle

We now investigate the behaviour of investments and capacity utilisation across the business cycle. Previous research has shown that firm-level investment and its spikes depend upon the business cycle (Grazzi, Jacoby and Treibich, 2016; Bachmann, Elstner and Hristov, 2017). In expanding episodes of the economy, strong growth motivations increase firms' desire to invest in production capacity. However, consecutive periods of tightness reduce such motivations and decrease the available credit for the firms. Figure 4(a) demonstrates the annual share of firms with investment spikes featuring a significant investment decline up to 2014, coinciding with the European debt crisis. Since 2014, a recovery pattern similar to findings in the literature (OECD, 2021; Ciapanna et al., 2020; Mohades and Savona, Forthcoming) has been observed, returning to pre-2007 values. A large part of this recovery can be attributed to the manufacturing sector and through policies that incentivised new technology and innovative investments (ISTAT, 2018).[15] After all, spikes in investments can be due to purchasing plants and machines that complement innovative-related activities. In addition to firms' investments, capacity utilisation depends on the business cycle (Fagnart, Licandro and Portier, 1999). In the graph below, we demonstrate the annual average of capacity utilisation and show how it strongly co-moves with the business cycle, indicated by large drops during recessionary periods. A persistent and sizable drop after the Great Recession is also evident here, whereby capacity utilisation remains lower compared to pre-2008 levels between 2014 and 2018.



(a) Annual share of firms with investment spikes

(b) Annual average of firms' capacity utilisation

Figure 4: Investment spikes and capacity utilisation of Italian firms vs business cycle from 2002-2024. Data source: Survey of Industrial and Service Firms, Bank of Italy (2024).

Therefore, we can see a pro-cyclical pattern in investments and capacity utilisation on average. At the beginning of non-recessionary episodes, firms overuse their capacity to cope with demand and avoid adjustment costs. After the initial phase of the boom, firms begin investing and hiring to maintain a capacity buffer that can cover unforeseen future events. During recessions, firms often refrain from adjusting their capital and, consequently, reduce their adjustment costs by lowering the capacity utilisation rate. As the economy recovers, more and more inputs are used until the capacity utilisation target is reached again.

While it is expected that sectors with costly adjustments[16] of capacity utilisation would behave differently from the norm, we cannot document evidence of a sizeable sector-level heterogeneity of the capacity utilisation target. Table A.7 in Appendix B.8 presents these targets for each sector and each state of the economy. The difference between sectors' targets barely reaches 3% in each business cycle phase. The primary reason for this result is the persistence of low capacity utilisation in non-recessionary periods following the Great Recession. The structural break that moved the average from almost 80% to 75% seems to have been quite persistent, as well as the macroeconomic indicators of the Italian economy, as also presented previously in Figures 1 & 4(b). Despite this low difference, we detect a pattern in which the business cycle impacts the sectoral target of capacity utilisation. We observe a higher capacity utilisation for 6 out of 7 manufacturing industries during the non-recessionary periods.

Figure A.2 in Appendix B.8 provides more context on the sector-level heterogeneity of capacity utilisation in different business cycle phases. While most sectors' capacity utilisation co-move across the business cycle, sectors SS4 (Processing of non-metallic minerals) and SS7 (Energy and extraction) were hit more severely during the European debt crisis. Sector SS2 (Textiles, clothing, and leather and footwear products) was hit

[15]These policies primarily included banner Impresa 4.0 and Transizione 4.0, which attempted to offset the high regulatory burdens and levels of uncertainty faced by firms (OECD, 2021). Investment in assets supported and favoured by these policies, such as R&D and software and analytics, has proliferated following the introduction of these policies after the European debt crisis (Mohades and Savona, Forthcoming).

[16]Some forms of production require the plant to operate non-stop as the cost of simply turning the machinery on and off is too high. Production of cement is a well-known example of such industries.

the hardest during the Covid crisis, as it suffered from multiple lockdowns, decreased consumption, and excess stock (Leal Filho et al., 2023; Arania, Putri and Saifuddin, 2022).

Lastly, we ask whether our uncertainty measure behaves as expected in relation to the business cycle. We average the values of our uncertainty measure over the years and find that our uncertainty measure peaks during the recessions, similar to the original overall uncertainty index in Mohades, Piccillo and Treibich (2024). The local peaks during the Great Recession, the European debt crisis, and the COVID-19 outbreak reflect how this uncertainty measure behaves countercyclically in relation to the business cycle. Furthermore, this measure correlates with a magnitude of 0.52 to EPU, as reported by Baker, Bloom and Davis (2016). A graph of annual sales uncertainty for the Italian manufacturing sector is provided in Appendix B.10.

We are now ready to discuss the results and implement the variables introduced and explored in this section in the empirical model presented in Section 3.

5 Results

This section presents the results of our estimations based on the equations given in Section 3 and the implementation of the variables introduced in Section 4. Initially, our framework tests whether firms' investments and the probability of experiencing a spike are sensitive to being at the growth window and the distance to the target. Based on the predictions of our conceptual framework in Section 2, we expect both the overcapacity dummy and the capacity utilisation gap to display positive coefficients in relation to investment rates and spikes. Table 2 displays our results from both regressions with the investment rate and the probability of spike as dependent variables:

	Dependent Variable			
	Inv Rate ($I_{i,t}/\bar{Y}_{i,t-1}$)		Spike (S)	
$(CU_{i,t} - CU^{\psi}_{s,\tau})$	0.003		0.006*	
	(0.003)		(0.002)	
$O_{i,t}$		0.209*		0.136*
		(0.091)		(0.067)
$\pi_{i,t-1}$	0.348***	0.336***	0.294***	0.302***
	(0.101)	(0.101)	(0.078)	(0.078)
$L^{G}_{i,t-1}$	-0.026	-0.048	0.394	0.392
	(0.372)	(0.372)	(0.260)	(0.260)
Constant	3.013***	2.903***		
	(0.081)	(0.093)		
Estimation Method	OLS	OLS	Clogit	Clogit
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Firms	3,666	3,666	916	916
Observations	25,196	25,196	9,314	9,314

Table 2: Regression Results For Equation 1

*** Significant with 99% Confidence Interval, ** Significant with 95% Confidence Interval, * Significant with 90% Confidence Interval. For spikes, the sample is reduced to firms that experienced at least one spike during the period of our analysis.

We document that observing a higher capacity utilisation distance from the target and presence at the growth window increases the probability of observing a spike or higher investment rates, in line with the "fork in the road" theory (Brown and Mawson, 2013; Coad et al., 2021). Therefore, firms at higher capacity are more likely to experience an investment spike and expand. Past profitability also positively contributes to both investment rates and spikes, indicating that Italian firms have been utilising internal funds to finance their investments, consistent with the findings of Ughetto (2008).

In a second step, corresponding to the theoretical framework explained in Section 2, we aim to investigate the impact of financial constraints and uncertainty on investment decisions, the probability of spikes, and their interaction with firms' capacity utilisation. While there is less discrepancy on the impact of financial constraints on firms' investments, there is substantial disagreement regarding the effect of uncertainty on investments, especially large investments (spikes). Previously, the literature has shown that the presence of irreversibility and higher uncertainty reduces the responsiveness of investment to demand shocks (Bloom, Bond and Van Reenen, 2007; Bloom, 2009; Bond and Lombardi, 2006). Hence, firms become more cautious when investing or adjusting inputs to minimise dead-weight losses in uncertain times. On the other hand, low uncertainty can trigger firms' risk-taking actions to benefit from the investing premium (Bo and Lensin, 2005) and encourage firms to take replacement investments (Mauer and Ott, 1995). The results corresponding to Equation 4 are provided below:

	Dependent Variable: Investment Rate ($I_{i,t}/\bar{Y}_{i,t-1}$)			
	(1)	(2)	(3)	(4)
$(CU_{i,t} - CU^{\psi}_{s,\tau})$	0.005	0.005		
	(0.004)	(0.004)		
$O_{i,t}$			0.369**	0.366**
			(0.112)	(0.112)
$FC_{i,t}$	-0.635**	-0.514**	-0.633*	-0.427
	(0.207)	(0.199)	(0.257)	(0.248)
$U_{s,t}$	0.016*	0.017*	0.031**	0.029**
	(0.007)	(0.007)	(0.010)	(0.009)
$O_{i,t} \times FC_{i,t}$			0.033	-0.189
			(0.322)	(0.311)
$FC_{i,t} \times (CU_{i,t} - CU^{\psi}_{s,\tau})$	0.008	0.001		
	(0.009)	(0.009)		
$O_{i,t} \times U_{s,t}$			-0.030*	-0.024
			(0.013)	(0.013)
$(CU_{i,t} - CU^{\psi}_{s,\tau}) \times U_{s,t}$	-0.001	-0.001		
	(0.001)	(0.001)		
$U_{s,t} \times FC_{i,t}$	-0.024	-0.039	-0.031	-0.036
	(0.024)	(0.023)	(0.024)	(0.023)
$\pi_{i,t-1}$	0.336***	0.344***	0.325**	0.334***
	(0.101)	(0.101)	(0.101)	(0.101)
$L^{G}_{i,t-1}$	-0.033	-0.009	-0.054	-0.028
	(0.369)	(0.369)	(0.369)	(0.369)
$U_{s,t-1}$	0.030***	0.029***	0.031***	0.030***
	(0.007)	(0.007)	(0.007)	(0.007)
Constant	2.849***	2.836***	2.647***	2.637***
	(0.095)	(0.095)	(0.113)	(0.112)
Instrument for $FC_{i,t}$	-	$FC_{i,t-1}$	-	$FC_{i,t-1}$
Hausman Test	$\overbrace{\hspace{4em}}^{\checkmark}$		$\overbrace{\hspace{4em}}^{\checkmark}$	
Estimation Method	OLS	OLS	OLS	OLS
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Firms	3,666	3,666	3,666	3,666
Observations	25,193	25,193	25,193	25,193

Table 3: Regression Results For Equation 2

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

	Dependent Variable: Probability of Spike (S)			
	(1)	(2)	(3)	(4)
$(CU_{i,t} - CU^{\psi}_{s,\tau})$	0.009**	0.009**		
	(0.003)	(0.003)		
$O_{i,t}$			0.257**	0.259**
			(0.084)	(0.080)
$FC_{i,t}$	-0.478**	-0.308	-0.357	-0.077
	(0.163)	(0.159)	(0.214)	(0.189)
$U_{s,t}$	0.010*	0.009	0.023**	0.017**
	(0.005)	(0.004)	(0.008)	(0.006)
$O_{i,t} \times FC_{i,t}$			-0.159	-0.518*
			(0.271)	(0.251)
$FC_{i,t} \times (CU_{i,t} - CU^{\psi}_{s,\tau})$	-0.003	-0.007		
	(0.008)	(0.008)		
$O_{i,t} \times U_{s,t}$			-0.023*	-0.018*
			(0.010)	(0.009)
$(CU_{i,t} - CU^{\psi}_{s,\tau}) \times U_{s,t}$	-0.001	-0.001		
	(0.001)	(0.001)		
$U_{s,t} \times FC_{i,t}$	-0.004	0.004	-0.014	0.010
	(0.014)	(0.016)	(0.015)	(0.016)
$\pi_{i,t-1}$	0.284***	0.294***	0.293***	0.301***
	(0.078)	(0.078)	(0.078)	(0.078)
$L^{G}_{i,t-1}$	0.376	0.399	0.359	0.395
	(0.261)	(0.261)	(0.262)	(0.261)
$U_{s,t-1}$	0.011**	0.011**	0.011**	0.011**
	(0.004)	(0.004)	(0.004)	(0.004)
Instrument for $FC_{i,t}$	-	$FC_{i,t-1}$	-	$FC_{i,t-1}$
Hausman Test	✓		✓	
Estimation Method	CLogit	CLogit	CLogit	CLogit
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Firms	916	916	916	916
Observations	9,312	9,312	9,312	9,312

Table 4: Regression Results For Equation 2

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

In Tables 3 & 4, we show that being present at the growth window (shown by O) increases both investment rates and the probability of investment spikes. The distance to the target has a positive impact on the probability of a spike in investments, even after accounting for financial constraints, uncertainty, and controlling for past uncertainty, profitability, and employee growth. Importantly, these results display a different pattern for the Italian firms within our sample compared to those studied by Bottazzi, Secchi and Tamagni (2008) from 1998 to 2003, indicating that higher incentives for investment are associated with Italian firms that have higher motives for growth. Presence at the growth window increases both investment rates and the probability of observing a spike, and Italian firms are not an exception, despite the difficulties of investment.

Interestingly, unlike other empirical exercises in the literature, we find that uncertainty, on average, is positively associated with investment rates and spikes across firms, as revealed by the positive coefficient of $U_{s,t}$. However, being present at the growth window cancels out this positive effect, as shown by the sum of the coefficient of $U_{s,t}$ and the coefficient of $O_{i,t} \times U_{s,t}$. Our results on the positive impact of uncertainty on firms' investments are particularly noteworthy, given the nature of our sample. In environments where firms, on average, operate below capacity, the adverse effects of uncertainty on investments can be significantly smaller (Dangl, 1999). Furthermore, we interpret this heterogeneous impact of uncertainty on firms at and outside the growth window as inefficiency in allocating inputs, since firms outside the growth window continue to invest when uncertainty is high, similar to Bansal et al. (2019). These effects are potentially driven by different values of the elasticity of substitution in the production and consumption of products from high- and low-potential growth firms (Dellas and Fernandes, 2006). In addition, demand uncertainty is previously found to have a lower impact on firms' investments than other sources of uncertainty (Fuss and Vermeulen, 2008).

Furthermore, we demonstrate a robust negative impact of financial constraints on both investment rates and the likelihood of spikes, similar to Kamber, Smith and Thoenissen (2015), among others. Alfaro, Bloom and Lin (2024) demonstrates how more financially constrained firms cut their investments more than less constrained ones following a shock. Furthermore, they suggest that financial constraints can account for a significant portion of the decline in output following a shock.

5.1 Potential Mechanisms

To better understand the mechanism behind our model, we limit the sample to observations with below-median uncertainty and no financial constraints. The rationale is based on the idea that firms without tight external conditions represent an important group for whom the role of being present at the growth window should be robustly positive. Additionally, for these firms, desired and realised investment should better align, and their capacity needs should more directly drive their investment plans. We find evidence in this small subsample that presence at the growth window increases the probability of observing a spike. While we expected a stronger coefficient for both the gap and overcapacity dummies for both investment variables, the small sample size limits the insights we can draw from these analyses, as the standard deviations increase. These results are provided in Online Appendix A.1.

Suppose both the gap to the capacity utilisation target and overcapacity significantly affect investment. In that case, firms operating in the growth window (operating at overcapacity) should show the strongest investment response when their distance to the target is larger. The intensity captures how strongly this joint condition (being in the growth window and far from the target) drives investment. To study this intensity effect, we add the interaction term between gap ($CU_{i,t} - CU^{\psi}_{g,\tau}$) and overcapacity dummy ($O_{i,t}$) to our regressions, with results presented in Online Appendix A.2. Our regressions in this section cannot reject the hypothesis of incorporating both the gap to the capacity utilisation target and the growth window dummy: being farther ahead of the capacity utilisation target, on average, increases the probability of a spike occurrence among firms. We do not find evidence of a significant intensity difference between these groups in their reaction to the gap-to-capacity target. However, our baseline results remain relatively robust in the presence of this interaction term.

Although the results of our analyses regarding no heterogeneity may seem against the odds, we believe that in a sample including small and medium enterprises (SMEs) with high potential growth, there might be more layers of heterogeneity regarding the intensity of being present at the growth window, as new firms usually operate at very high capacity and invest and grow.

5.2 Small, Medium and Large: Which gazelle to hunt?

In what follows we investigate the role of firm size in our framework, and divide our sample into small (less than 100 employees), medium (between 100 and 250 employees) and large firms (more than 250 employees). The descriptive statistics provided in Table A.4 in Appendix B.5 also show that larger firms have a higher capacity utilisation and are more often present at the growth window than the group of small firms.

	Investment Rate ($I_{i,t}/\bar{Y}_{i,t-1}$)			Probability of Spike (S)		
	Small	Medium	Large	Small	Medium	Large
$O_{i,t}$	0.146	0.600**	0.458*	0.166	0.233	0.429**
	(0.181)	(0.186)	(0.227)	(0.134)	(0.154)	(0.154)
$FC_{i,t}$	-0.405	-0.203	-1.347**	-1.224**	-0.050	-0.752*
	(0.304)	(0.318)	(0.443)	(0.391)	(0.309)	(0.333)
$U_{s,t}$	0.029*	-0.004	0.016	0.017*	0.021	0.002
	(0.013)	(0.013)	(0.013)	(0.007)	(0.011)	(0.008)
$O_{i,t} \times FC_{i,t}$	0.246	-0.034	-0.319	0.107	-0.871	-0.729
	(0.469)	(0.497)	(0.718)	(0.389)	(0.520)	(0.532)
$O_{i,t} \times U_{s,t}$	0.002	-0.076***	-0.046	-0.017	-0.030	-0.014
	(0.022)	(0.023)	(0.025)	(0.013)	(0.018)	(0.015)
Instrument for $FC_{i,t}$	$FC_{i,t-1}$	$FC_{i,t-1}$	$FC_{i,t-1}$	$FC_{i,t-1}$	$FC_{i,t-1}$	$FC_{i,t-1}$
Estimation Method	OLS	OLS	OLS	CLogit	CLogit	CLogit
Time FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Firms	1,772	1,643	1,091	372	346	250
Observations	8,727	8,663	7,803	3,041	3,002	2,410

Table 5: Regression results for Investment Rate and Investment Spikes, by firm size

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The results for the other independent variables of these regressions, as well as for the gap to capacity utilisation, can be found in the Online Appendix.

Table 5 shows that medium and large firms increase their investment rate in response to being present at the growth window, while only large firms significantly increase their probability of having a spike. Instead, smaller firms do not react significantly to being at the growth window. This may be because the marginal costs of growth are decreasing with firm size (Coad et al., 2021), for example, finding the right capital or employees to support their growth is more difficult for smaller than for large firms. For small firms, these costs might be deterring investment, even when they operate over their capacity utilisation threshold. In addition, smaller firms typically have a lower willingness to borrow, and are more financially constrained, which might drive the lack of response to overcapacity. However, our results from Table 5 do not support this hypothesis. The role of uncertainty seems instead to depend on firm size. Higher uncertainty is positively associated with investments only among smaller firms. A classical explanation can be the limited information available to smaller firms before their investment planning, as explained by Barry and Brown (1986). Yet, the interaction between the overcapacity dummy and uncertainty ($O_{i,t} \times U_{s,t}$) is significant and negative only for medium-size firms - in uncertain times, the impact of being at the growth window is entirely cancelled for this group, in accordance with real-options theory (Dixit and Pindyck, 1994; Bloom, Bond and Van Reenen, 2007).

6 Robustness Checks

This section reviews multiple checks we perform to ensure the robustness of our baseline specification explored and discussed in Sections 3 to 5. We perform checks to address issues related to the survey timing (within-year expectation vs realised). We introduce alternative specifications for investment rate, capacity utilisation gap and uncertainty measurements to test the validity of our approach. We then study whether our results are driven by the frontier firms as discussed by Añón Higón et al. (2022). Lastly, we will explain why we believe the results presented in our analyses are not driven by the entries and exits of firms.

The Bank of Italy distributes and collects the Survey of Industrial and Service Firms annually between January and May. Hence, our observations' values are the expected sales and investments within the year of the study. Due to such timing, one may be concerned that the within-year expectations might be incorrect or subject to the business cycle beliefs. We assess this issue by incorporating the realised values that firms report in the year after. Our main results remain robust to this new specification. Given the coefficients reported in Online Appendix B.1, and the high pairwise correlation between the baseline variable and the lagged realised value from the following year, we can conclude that our results are robust to within-year business cycle developments that might affect managers' expectations. The robustness of these findings can be attributed to firms' awareness of their annual orders and investment decisions, particularly given that the sample is predominantly composed of medium to large firms.

Throughout our analyses, we normalise the raw investment values by the average of the current and 1-year lagged sale values. To avoid the issue of persistent sales cycles impacting these values, we also run our regressions with the investment rate normalised by the current average and the past two years, hence three years in total ($t, t+1, t+2$). The regression results are presented in Online Appendix B.2.1. In Online Appendix B.2.2, we provide the results of our regressions with the investments normalised by labour (in year t) instead of sales. In both of these alternative analyses, we can find evidence of the robustness of our proposed framework in Sections 2 & 3. Therefore, we conclude that the unique method of normalising investments is not solely driving the previously presented results, and our approach is robust in terms of defining the investment rate.

Our baseline specification considers three dimensions of variation in the gap variable ($CU_{i,t} - CU^{\psi}_{s,\tau}$): variation of the realised capacity utilisation across firms, time and across sectors and regimes (recessionary and non-recessionary). However, the low variation of the target (11 industries and two regimes) might weaken our findings. We test our model using a firm-specific target (the firm-specific average in different regimes) to determine how robust our baseline specification is against this potential bias. In Online Appendix B.2.3, we provide the results using a firm-specific target instead of a sector-specific one. This construction can be formally stated as a firm-specific capacity target ($CU_{i,t} - CU^{\psi}_{i,\tau}$) and its corresponding new overcapacity dummy $O^{\text{alt}}_{i,t}$ accordingly, where $O^{\text{alt}}_{i,t} = 1$ if $CU_{i,t} > CU^{\psi}_{i,\tau}$. Our analysis confirms the robustness of our baseline specification: regardless of the definition of the capacity target, deviation from the target or presence at the growth window motivates investments in plants and machinery. Therefore, we conclude that low variation due to aggregation at the sector level does not sabotage analysis.

In this section, we examine multiple measures of uncertainty derived from firms' sales records and expectations. In Section 5, we provided the results with uncertainty proxied by "sectoral volatility" ($U_{s,t}$) driven by sales volatility. However, our access to survey data enables us to utilise firms' expectations in calculating subjective uncertainty. We are not the first to emphasise the importance of firms' expectations in their investment behaviour due to uncertainty. Guiso and Parigi (1999) found that the cross-sectional subjective uncertainty of managers reduces investment.[17] Similarly, through measuring subjective uncertainty from survey data of the U.S manufacturing firms, Altig et al. (2022); Bloom et al. (2022) found a robust negative relationship between uncertainty and investment, as well as uncertainty and firms' sales growth and hirings[18]. We test our results

[17]Their results show substantial heterogeneity among firms. Additionally, limited access to reversible investments amplifies the impact of higher uncertainty on firms' investment decisions.

[18]They also find a strong positive correlation between firms' subjective uncertainty and their sales forecast error. Interestingly, flexible inputs show a positive relationship to uncertainty, demonstrating that businesses switch from less flexible to more flexible factor inputs at higher levels of uncertainty.

based on the firms' subjective uncertainty and forecast error. To compute subjective uncertainty, we use intuition from the method used in Lamorgese et al. (2024); Bloom et al. (2022); Bachmann et al. (2021), and use the size of the spectrum of their expected sales growth in $t + 1$ as a proxy for their uncertainty at time t. Namely, we use the difference between the maximum and minimum expected sales growth for the next period as:

$$\text{Subjective Uncertainty}_{i,t} \equiv SU_{i,t} = E_t^{\max}\text{Sales Growth}_{i,t+1} - E_t^{\min}\text{Sales Growth}_{i,t+1}$$

We also use the forecast error as a proxy for uncertainty, similar to Arslan et al. (2015). We have data regarding the point expectations of firms from their future sales growth. We then calculate the forecast error as follows:

$$\text{Forecast Error}_{i,t} \equiv FCE_{i,t} = \frac{E_t\text{Sales}_{i,t+1} - \text{Sales}_{i,t+1}}{\text{Sales}_{i,t+1}}$$

The results of these analyses are presented in Online Appendix B.3. We demonstrate that our main takeaways are robust to uncertainty measurement. However, our model performs relatively poorly when expectation-based uncertainty measures are used, as the response rates to the expected values are low compared to within-year values, and hence, the sample size is smaller.

We also suspect that our results may be driven by firms that are very large in our sample. The literature on firm dynamics in Italy has previously found considerable heterogeneity in growth and investment among frontier (leader) and other firms (Pozzi and Schivardi, 2016; Carpenter and Rondi, 2000). We construct a dummy based on the median number of employees to distinguish the very large firms that we believe coincide with the leaders, where Large $= 1$ *if* $EMP > Percentile(50)$. These results are presented in Online Appendix B.4 and highlight several key findings. First, large firms tend to invest more after controlling for firm and time-fixed effects. Second, larger firms that are financially constrained tend to invest more. However, our finding that firms at the growth window are vulnerable to uncertainty persists: even though we rule out the variation of investment rate and probability of spike due to being very large, the inefficiency due to uncertainty remains predominant. Firms with low potential growth invest more, while those with high potential and higher efficiency do not, even after controlling for the effect of frontier firms.

One might raise the concern that the macroeconomic dynamics displayed in Figures 1 and 4(b) may be accompanied by and result from firms' exits and entries. On average, capacity utilisation surges once there are many entrants in the market. Firms that exit usually display lower utilisation rates before leaving due to lower activity in the last years of business. Therefore, the persistently low values of capacity utilisation after the Great Recession might have resulted from many firms exiting and few entering. While the Great Recession has significantly impacted market dynamism in Italy, entries and exits have been affected similarly, with a downward trend of a similar magnitude. Meanwhile, the change in market dynamism that could have driven capacity utilisation downwards would be an increasing difference between entries and exits, rather than lower market dynamism resulting from both lower entries and exits.

Figure A.3 in Appendix B shows that the post-crisis market environment in the Italian economy has failed to show dynamism, as both entry and exit rates have dropped excessively compared to pre-recession (2007). If the firms' entry index was on the same cycle as capacity utilisation and its deviation from the target presented in our paper, one could claim that the dynamics between 2014 and 2020 were driven by young firms that operate at high capacity. However, as shown in this figure, this is not the case, and the entries and exits have mainly remained irrelevant in explaining the changes in capacity utilisation after the European debt crisis.

7 Conclusion

Throughout the paper, we have identified a new mechanism to explain the relationship between capacity utilisation and investments, considering the role of uncertainty and financial constraints. While firms at the growth window are willing to invest, financial constraints and uncertainty have limited investments in high-growth potential firms due to financial constraints. Notably, firms outside the growth window have increased their investments in times of uncertainty, creating inefficiencies. Lastly, our results are driven by medium and large firms.

Our findings carry high micro and macroeconomic importance. Firstly, our analysis contributes to explaining the low level of firm investments in the Italian economy over recent decades (Bond, Rodano and Serrano-Velarde, 2015). While we observe a declining pattern in firms' capacity use and investments until 2014, a slight recovery towards the pre-Great Recession values can be observed in both variables after 2014. This result aligns with previous literature findings, which offer multiple explanations for this recovery (OECD, 2021; Ciapanna et al., 2020). The results of our analyses also have significant implications for industrial policy, which could support firms during their growth window. Identifying and understanding these trigger points can inform the development of cost-effective strategies to stimulate investment precisely when hesitant firms are at the critical growth window. Our findings also validate previous research on the role of financial constraints in deterring firms' investments. During periods of heightened borrowing constraints, such as recessions, allocating funds more effectively is needed by identifying firms with greater growth potential. Lastly, our discovery of the heterogeneous impact of uncertainty for firms with different levels of capacity utilisation could motivate the monitoring and mitigation of high uncertainty levels in the economy, to prevent the inefficient allocation of resources to firms outside their growth window.

Future research should aim to understand the theoretical mechanisms associated with expansion, uncertainty, and capacity utilisation under different financial constraint regimes. This may be achieved by setting up a model in which firms' investment behaviour could depend on various features of the firm and the state of the economy regarding investments and borrowing. Furthermore, it would be essential to increase the coverage of data on capacity utilisation of firms, extending the survey used in this paper to a larger share of the Italian economy, or to other contexts. This would allow to test a larger range of mechanisms and sources of heterogeneity in explaining the complex relation between capacity utilisation and firm investment.

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A Estimation Method: Panel Logit ML

Following Greene (2018), let $i = 1, 2, \ldots, n$ denote firms and $t = 1, 2, \ldots, T_i$ represent the observations for the ith firm. The dependent variable, y_{it}, takes a binary value of 0 or 1, corresponding to whether an investment spike or financial constraints are present. The vector $\mathbf{y}_i = (y_{i1}, \ldots, y_{iT_i})$ represents the outcomes for the ith firm, while $\mathbf{x}_{it}$ is a row vector of covariates. Let k_{1i} denote the observed number of ones for the dependent variable within the ith firm, expressed as:

$$k_{1i} = \sum_{t=1}^{T_i} y_{it}$$

Thus, there are k_{1i} cases matched to $k_{2i} = T_i - k_{1i}$ controls within the ith group. According to Hosmer Jr, Lemeshow and Sturdivant (2013), the probability of observing $\mathbf{y}_i$ conditional on $\sum_{t=1}^{T_i} y_{it} = k_{1i}$ is:[19]

$$\Pr\left(\mathbf{y}_i \,\middle|\, \sum_{t=1}^{T_i} y_{it} = k_{1i}\right) = \frac{\exp\left(\sum_{t=1}^{T_i} y_{it}\mathbf{x}_{it}\boldsymbol{\beta}\right)}{\sum_{\mathbf{d}_i \in S_i} \exp\left(\sum_{t=1}^{T_i} d_{it}\mathbf{x}_{it}\boldsymbol{\beta}\right)}$$

Here, d_{it} takes values of 0 or 1, with $\sum_{t=1}^{T_i} d_{it} = k_{1i}$, and S_i represents the set of all possible combinations of k_{1i} ones and k_{2i} zeros. Although there are $\binom{T_i}{k_{1i}}$ such combinations, the denominator of the above equation can be computed recursively without enumerating all combinations.

Let the denominator be denoted by:

$$f_i(T_i, k_{1i}) = \sum_{\mathbf{d}_i \in S_i} \exp\left(\sum_{t=1}^{T_i} d_{it}\mathbf{x}_{it}\boldsymbol{\beta}\right)$$

Computationally, the recursive formula for f_i as the number of observations increases is given by:

$$f_i(T, k) = f_i(T-1, k) + f_i(T-1, k-1)\exp(\mathbf{x}_{iT}\boldsymbol{\beta})$$

with the initial conditions $f_i(T, k) = 0$ if $T < k$ and $f_i(T, 0) = 1$.

The conditional log-likelihood function is then expressed as:

$$\ln L = \sum_{i=1}^{n}\left(\sum_{t=1}^{T_i} y_{it}\mathbf{x}_{it}\boldsymbol{\beta} - \log f_i(T_i, k_{1i})\right)$$

The derivatives of the conditional log-likelihood function can also be obtained recursively by differentiating the recursive formula for f_i. A maximum likelihood approach estimates the coefficients that maximise the log-likelihood function above.

[19] The extensive derivation of the probability function is outside of our scope. For a detailed derivation, please refer to Hosmer Jr, Lemeshow and Sturdivant (2013) or Greene (2018).

B Additional Graphs and Tables

B.1 Aggregate Capacity Utilisation and Investments

(a) Capacity utlisation (b) Aggregate investment

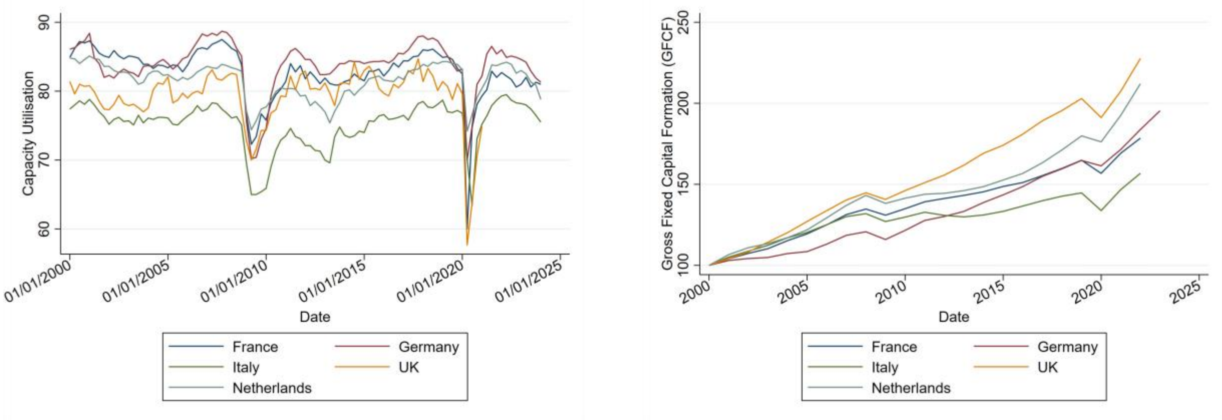

Figure A.1: Positive relationship between aggregate annual investments and quarterly capacity utilisation at the country level. Data source: Business Tendency Survey, OECD (2024). Investment data for some countries is only available at an annual frequency.

B.2 Sectoral Division of the Survey of Industrial and Service Firms Data

Variable	Values	Description	ATECO 2002	ATECO 2007	NACE
settor11	SS1	Food industries, beverages, and tobacco products	DA	10, 11, 12	C10-C12
	SS2	Textiles, clothing, and hide, leather, and footwear products	DB, DC	13, 14, 15	C13-C15
	SS3	Coke manufacturing, chemical industry, rubber, and plastics	DF, DG, DH	19, 20, 21, 22	C19-C21
	SS4	Processing of non-metallic minerals	DI	23	C22-C23
	SS5	Metal engineering industry	DJ, DK, DL, DM	24, 25, 26, 27, 28, 29, 30, 33	C24-C25
	SS6	Other manufacturing industries	DD, DE, DN	16, 17, 18, 31, 32	C16-C18,C26-C33,E
	SS7	Other industries excluding construction	CA, CB, CE	05, 06, 07, 08, 09, 35, 36, 37, 38, 39	D
	SS8	Wholesale and retail commerce	G	45, 46, 47	G45-G46
	SS9	Hotels and restaurants	H	55, 56	I
	SS10	Transport and communications	I	49, 50, 51, 52, 53, 58, 59, 60, 61, 62, 63	H,J
	SS11	Real estate activities, IT, etc.	K	68, 69, 70, 71, 72, 73, 74, 75, 77, 78, 79, 80, 81, 82	L,M,N

Table A.1: Sector categorisation for the *settor11* variable in the Survey of Industrial and Service Firms dataset and its comparability to ATECO by ISTAT.

B.3 Correlation Matrix

	$Y_{i,t}$	$L_{i,t}$	$I_{i,t}$	$I_{i,t}/\bar{Y}_{i,t-1}$	$S_{i,t}$	$CU_{i,t}$	$CU_{i,t} - CU^{\psi}_{s,t}$	$O_{i,t}$	$FC_{i,t}$	$\pi_{i,t}$	$U_{s,t}$	$U_{i,t}$	$L^G_{i,t}$
$Y_{i,t}$													
$L_{i,t}$	0.56*												
$I_{i,t}$	0.72*	0.67*											
$I_{i,t}/\bar{Y}_{i,t-1}$	-0.00	0.00	0.03*										
$S_{i,t}$	-0.01*	0.01*	0.08*	0.20*									
$CU_{i,t}$	-0.02*	-0.01*	-0.00	-0.02*	0.01*								
$CU_{i,t} - CU^{\psi}_{s,t}$	-0.02*	-0.02*	-0.00	-0.02*	0.01*	0.99*							
$O_{i,t}$	-0.00	0.01*	-0.00	-0.00	0.01	0.70*	0.70*						
$FC_{i,t}$	-0.01*	-0.02*	-0.02*	-0.01*	-0.03*	-0.11*	-0.10*	-0.08*					
$\pi_{i,t}$	0.02*	0.02*	0.03*	-0.01	0.02*	0.20*	0.19*	0.16*	-0.13*				
$U_{s,t}$	0.03*	0.03*	0.04*	0.00	0.04*	-0.03*	-0.02*	-0.05*	0.02*	-0.01			
$U_{i,t}$	0.00	-0.01	0.00	0.04*	0.01*	-0.07*	-0.07*	-0.03*	0.02*	-0.04*	0.13*		
$L^G_{i,t}$	-0.01	0.00	-0.00	0.02*	0.03*	0.10*	0.10*	0.09*	-0.05*	0.12*	-0.00	-0.02*	
Rec	0.00	0.00	0.01	0.01	-0.01	-0.05*	0.00	-0.02*	0.04*	-0.09*	0.19*	0.03*	-0.01

Table A.2: Correlation Matrix. * denotes the 95% significance level

B.4 Summary Statistics for Growth Window and Non-Growth Window

	Growth Window Firms (GW)			Non-Growth Window Firms (NGW)			t-test
Variable	Mean	SD	N	Mean	SD	N	
Raw Variables							
$Y_{i,t}$	297,904.70	3,822,909.00	28,850	310,292.90	3,815,190.00	23,424	GW > NGW
$I_{i,t}$	8,184.02	74,619.18	23,063	8,413.82	87,432.89	15,862	GW > NGW
$L_{i,t}$	327.34	874.17	28,850	302.90	1,577.68	23,424	GW > NGW
$CU_{i,t}$	86.13	7.31	28,850	64.97	13.80	23,424	GW > NGW
Constructed Variables							
$I_{i,t}/\bar{Y}_{i,t-1}$	3.57	20.97	23,063	3.75	33.53	15,859	GW = NGW
$S_{i,t}$	0.10	0.30	23,063	0.10	0.30	15,859	GW = NGW
$CU_{i,t} - CU^{\Psi}_{s,t}$	9.44	7.36	28,850	-11.63	13.71	23,424	GW > NGW
$FC_{i,t}$	0.05	0.21	28,850	0.09	0.28	23,424	GW < NGW
$\pi_{i,t}$	0.76	0.43	26,607	0.62	0.49	21,277	GW > NGW
$U_{s,t}$	4.45	5.55	27,518	5.07	7.51	22,898	GW > NGW
$L^G_{i,t-1}$	0.01	0.11	18,955	-0.01	0.11	15,932	GW > NGW

Table A.3: Summary Statistics for Growth Window Firms and Non-Growth Window Firms

B.5 Summary Statistics for Different Firm Types (Size Heterogeneity)

	Small (< 100 employees)			Medium (100 – 249 employees)			Large (≥ 250 employees)		
Variable	Mean	SD	N	Mean	SD	N	Mean	SD	N
$Y_{i,t}$	25023.01	152772.10	39,620	93184.84	499253.10	14,759	1034892	7171573	13,283
$I_{i,t}$	782.10	1822.33	14,176	1875.81	4760.53	14,045	24185.44	135740.80	12,369
$L_{i,t}$	47.40	21.57	39,620	156.23	41.88	14,759	1016.63	2360.19	13,283
$I_{i,t}/\bar{Y}_{i,t-1}$	3.70	36.96	14,176	3.67	26.55	14,045	4.29	65.63	12,366
$S_{i,t}$	0.10	0.30	14,176	0.10	0.30	14,045	0.10	0.30	12,366
$CU_{i,t}$	75.13	15.88	26,969	77.58	14.17	14,751	78.32	14.09	13,282
$O_{i,t}$	0.49	0.50	26,969	0.58	0.49	14,751	0.64	0.48	13,282
$U_{s,t}$	4.42	5.61	37,823	4.63	5.79	14,096	5.05	7.05	12,688
$FC_{i,t}$	0.07	0.25	39,620	0.06	0.23	14,759	0.04	0.21	13,283
$\pi_{i,t-1}$	0.67	0.47	29,214	0.72	0.45	10,942	0.74	0.44	9,820
$L_{i,t-1}$	-0.00	0.11	24,866	0.01	0.11	9,624	0.01	0.10	9,186
Unique Firms	5,939			2,467			1,546		
Observations	39,620			14,759			13,283		

Table A.4: Descriptive Statistics by Firm Size

B.6 Autocorrelation of Uncertainty Measures

	Overall Uncertainty ($U_{i,t}$)	Sectoral Volatility ($U_{s,t}$)	$\text{SU}_{i,t}$	$FCE_{i,t}$
L1	0.1736*	0.1600*	0.2252*	0.0068
L2	0.0732*	0.0870*	0.0929*	0.0081
L3	0.0550*	0.2228*	0.0647*	0.0003
L4	0.0625*	0.0882*	0.0679*	0.0022

Table A.5: Autocorrelation Table of Uncertainty Measures

B.7 First-stage Regression

	Dependent Variable: $FC_{i,t}$
$FC_{i,t-1}$	0.334***
	0.051
Estimation Method	Clogit
Time FE	✓
Firm FE	✓
Observations	12,144

Table A.6: Regression Results For Equation 3

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

B.8 Capacity Utilisation Heterogeneity at the Sector Level

Sectors	Capacity Utilisation Target		
	Non-Recessionary	Recessionary	All Sample Mean
SS1 - Food industries, beverages and tobacco products	76.04	75.94	76.01
SS2 - Textiles, clothing, and hide, leather and footwear products	77.5	75.83	76.87
SS3 - Coke manufacturing, chemical industry, rubber and plastics	77.28	76.51	77.00
SS4 - Processing of non-metallic minerals	73.52	72.42	73.11
SS5 - Metal engineering industry	77.97	75.30	76.98
SS6 - Other manufacturing industries	77.56	76.34	77.12
SS7 - Other industries excluding construction (energy and extraction)	77.13	77.71	77.34
All Sectors	77.22	75.66	76.65

Table A.7: Sector-level average (target) for capacity utilisation taken from the Survey of Industrial and Service Firms database in annual frequency for 2002-2023 - divided by recessionary and non-recessionary periods.

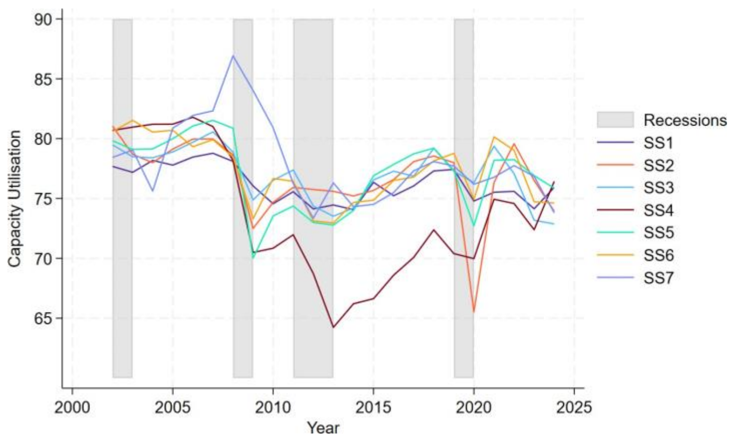

Figure A.2: Annual Average of Italian Manufacturing Sectors' Capacity Utilisation from 2002-2023. Data source: Survey of Industrial and Service Firms, Bank of Italy (2024)

B.9 Market Dynamics in Italy

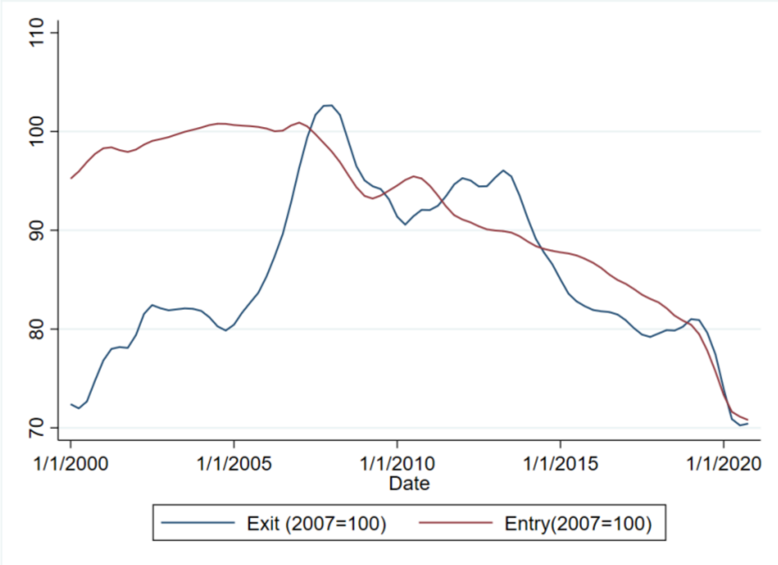

Figure A.3: Quarterly Exit and Entry (2007=100) of Italian Firms'. Data source: OECD

B.10 Sales Uncertainty

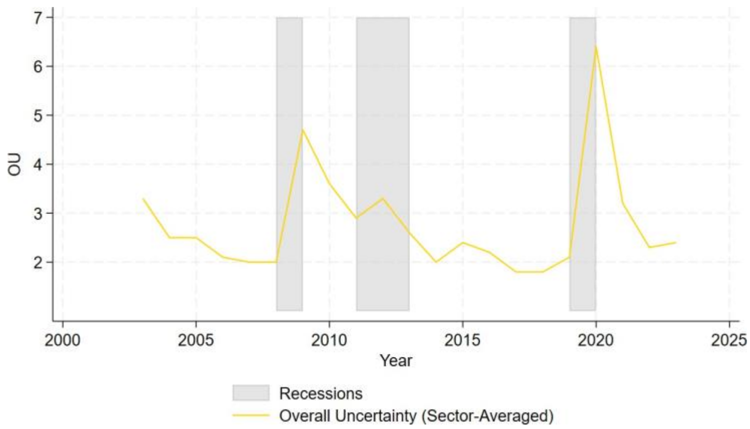

Figure A.4: Annual Average of Italian Manufacturing Firms' Overall Uncertainty from 2002-2023. Data source: Survey of Industrial and Service Firms, Bank of Italy (2024)

C Questions Used from the Survey of Industrial and Service Firms

- Investments in plant and machinery: "What is the extent of your investment in plant, machinery and equipment in the current year and next year"?
- Capacity Utilisation: Capacity Utilisation
- Sales: Turnover from year's sales of goods
- Profits: Please describe the firm's operating result (1 = large profit; 2 = small profit; 3 =broad balance; 4 = small loss; 5 =large loss.)
- Employees: Average Workforce

C.1 Construction of the Dummy *FC*

A major disagreement in the economic literature concerns the identification of firms that are financially constrained.[20] For instance, the work of Amiti and Weinstein (2018) uses a comprehensive, matched, lender-borrower data set covering all loans received from all sources by every listed Japanese firm over the period 1990–2010.[21] By surveying a group of CFOs in various geographical locations and using the matching procedure[22], Campello, Graham and Harvey (2010) find that constrained firms planned deeper cuts in tech spending, employment, and capital spending during the Great Recession of 2008. By measuring financial constraints using official credit ratings among a sample of Italian firms, Bottazzi, Secchi and Tamagni (2014) find that constrained firms have a lower chance of growth, as well as a higher chance of experiencing higher volatility. While their analysis demonstrates a substantial relationship between firm size and the chance of being constrained, Ferreira, Haber and Rorig (2023) find the presence of constrained firms[23] across the entire size distribution among Portuguese firms. However, they show that the presence of constraints among larger firms amplifies the impact of a financial shock.

In the Survey of Industrial and Service Firms questionnaire, firms are asked multiple questions that can be interpreted as being financially constrained [or not].

These questions include:

1. Please indicate whether, during 2021, at the interest rate and collateral terms applied to your firm, you wanted to increase your debt with banks or other financial intermediaries (Yes/No)

2. you were willing to accept more stringent loan terms (e.g. higher interest rate or more collateral) to increase the amount of borrowing (Yes/No)

3. in 2021, did you actually apply for new loans from banks or other financial intermediaries (Yes/No)?
   If three is yes:

   (a) you received the amount requested (Yes/No)

[20]Schiantarelli (1996) reviews the empirical approaches in measuring and identifying financial constraints using economic theory and/or firm-level data up to 1996. While the author expected that a common agreement would exist on empirically proxying financial constraints over time, various methods still exist to measure and identify the constraints that firms face when fin ancing their expansion projects.

[21]Their paper provides evidence that supply-side financial shocks - regardless of their measurement - greatly impact firms' investment.

[22]Instead of comparing the average difference in policy outcomes across all of the constrained and all of the unconstrained firms, they compare the differences in average outcomes of firms that are quite similar (i.e., matched) except for the "marginal" dimension of CFO-reported financial constraints. This yields an estimate of the differential effect of financial constraints on corporate policies across "treated" firms and their "counterfactuals

[23]Similar to Bottazzi, Secchi and Tamagni (2014), they also use credit information data to distinguish between constrained and unconstrained firms

(b) you were granted only part of the amount requested (Yes/No)

(c) you were given no loan because the financial intermediaries contacted were not willing to grant the loan (Yes/No)

(d) no loan was obtained for other reasons (e.g. cost or collateral considered to be excessive) (Yes/No)

If three is no:

(a) we did not contact banks or other intermediaries because we were convinced they would reject the application (Yes/No)

A summary of our construction can be found below:

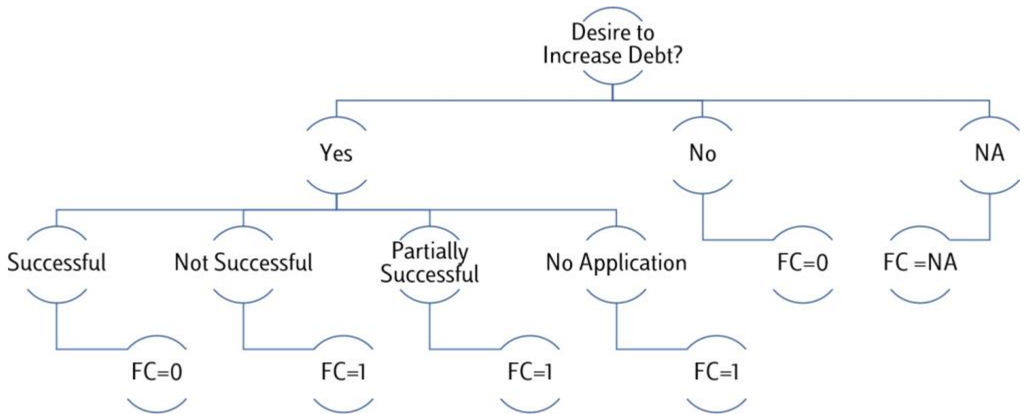

Figure A.5: Division of firms into financially constrained, unconstrained and unassigned