Essays on the role of uncertainty in the economy

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ESSAYS ON THE ROLE OF UNCERTAINTY IN THE ECONOMY

by

Amalia S. Jerison

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Abstract

In this dissertation, I study how uncertainty interacts with firm dynamics to affect aggregate economic variables. The first chapter proposes a measure of uncertainty based on forecaster surveys and compares it with another measure developed by Jurado, Ludvigson and Ng (2015). This chapter first investigates whether fluctuations in survey composition make the survey uncertainty measure too dependent on the identity of participating forecasters. An extension of the Breusch and Pagan (1979) test due to Breitung, Roling and Salish (2016) rejects constancy of parameters in regressions of GDP growth on survey uncertainty as the subsets of the forecasters differ. However, the predictions for GDP growth from the regressions do not vary much depending on which subset of the forecasters is used, suggesting that the survey uncertainty measure does not depend so much on composition as to make it uninformative. Next I compare the survey uncertainty measure with the financial uncertainty measure constructed by Ludvigson, Ma and Ng (2016) based on the method of Jurado, Ludvigson and Ng (2015), in terms of their relationships with GDP growth. The relationship between GDP growth and the financial uncertainty measure is found to have two structural breaks over the period 1980-2016. When the sample period is divided into three sub-periods delimited by the break dates, the coefficients on financial uncertainty in the GDP growth equation of a VAR change dramatically across periods. The change in the coefficients on survey uncertainty are less pronounced, possibly because it has a weaker association with GDP growth in general. Because of this weaker association of the survey uncertainty measure with growth, I use Ludvigson, Ma and Ng’s (2016) measure of financial
uncertainty as my preferred measure in the second chapter.

In the second chapter I analyze the relationships among uncertainty, the job creation and destruction rates of entering and incumbent establishments and the job destruction rates of incumbent and exiting establishments. The goal is to find out to what extent uncertainty affects the hiring and firing of entering and exiting establishments, and how important these effects are to employment as a whole. Using variance decomposition, I find that the effect of uncertainty on hiring (firing) is disproportionately due to the effect on hiring (firing) by incumbents, as opposed to hiring by entrants (firing by exitors).

The third chapter of this dissertation incorporates endogenous entry and exit of firms into a DSGE model with time-varying variance of the aggregate productivity shock. I find impulse responses of economic variables to shocks to this variance, which I define as uncertainty in this chapter. I then compare these impulse responses to those of the same variables in a different economy where there is no entry or exit of firms. I find that the responses to shocks to uncertainty are generally more contractionary or less expansionary in the model with entry and exit than in the model without entry and exit.
Chapter 1

A Comparative Study of Two Measures of Uncertainty

1.1 Introduction

Various measures of economic uncertainty have been found to rise during periods of economic downturn (e.g. Bloom 2009, Jurado et al. 2015, Ludvigson et al. 2016, Bloom et al. 2014). These findings have led economists to ask whether higher uncertainty contributes exogenously to a recession or is simply a by-product of low growth (Ludvigson et al. 2016, Bloom et al. 2014, Bachmann and Bayer 2013). The latter possibility could arise from greater policy uncertainty during recessions, for example about whether the Federal Reserve will intervene with an expansionary policy, from the fact that recessions typically last a shorter time than expansions, so that there may be contradictory signals about when the recession will end, or from the uneven impact of the recession across the economy, which again may lead to disparate signals about when recovery will begin. The former possibility could come about from precautionary motives leading consumers to spend less, while at the same time firms may reduce investment, hiring and promotions, thinking that such actions will be difficult to reverse if demand continues to fall. In the studies of Bloom (2009) and
Bloom et al. (2014), the wait-and-see (or real options) effect interacts with fixed labor and capital adjustment costs and irreversibilities to produce a downturn after a positive shock to uncertainty.

The question whether uncertainty has a causal effect on economic growth is important to policymakers deciding whether to expend resources to try to reduce uncertainty. For instance, should the Federal Reserve pursue policies that lead to relatively predictable interest rates or money supply? Should Congress try to minimize changes in tax policy to limit uncertainty about revenues? Should policymakers in general target a growth rate with little variation? To answer these questions, the relationship between uncertainty and growth needs to be determined.

Jurado, Ludvigson and Ng (2015, JLN) develop a way to construct uncertainty from forecasts for many economic variables, using a large information set for each forecast. The uncertainty measures constructed in this way are then applied in Ludvigson, Ma and Ng (2016, LMN) to study the relationship between uncertainty and growth. Using structural VARs they find that financial uncertainty – average uncertainty about a set of 147 financial variables – has a causal effect on GDP growth, but that real activity uncertainty – average uncertainty about a set of real activity variables – rises as an effect of lower GDP growth.

This paper provides further evidence about how these uncertainty variables are related to growth. By looking for structural breaks in the relationship between uncertainty and growth, I find clues about what is causing the relationships to differ across time. I also consider a survey measure of uncertainty that is constructed using the same basic definition of uncertainty as JLN and LMN's measure, but uses subjective density forecasts made by professional forecasters instead of the principal-components forecasts of JLN and LMN. A structural break test in the regression of GDP growth on survey uncertainty finds no structural break over the period 1980-2016. In contrast, the same test using financial uncertainty reveals a structural break at the year 2000.
The two measures considered in this paper illustrate opposite ways of measuring uncertainty. The LMN measure is equal to the average of forecast standard deviations across a large number of series of financial variables, where each forecast is made using the same principal-components model. The survey measure is defined using the same basic concept as LMN, but the forecasts are “subjective” – for a given density forecast, we do not know what model, if any, was used to make it, though the SPF documentation provides some information on this. Forecasters report using autoregressive models, structural models and intuition as the basis of their forecasts.

In considering the effects of uncertainty, it may be important to distinguish between perceived uncertainty and the conditional variance of the variables of interest. Which of these concepts to consider in the estimation depends on what question we are trying to answer: Agents base their current actions in part on their perceived uncertainty (or risk) about the future, but realized outcomes depend both on these actions and on the realization of the “true” underlying uncertainty. If the goal is to quantify the causal effects of uncertainty on economic outcomes, it would make sense to use perceived uncertainty. The aggregated survey measure of uncertainty could be viewed either as a representation of different perceptions of uncertainty held by agents in the economy, or as the uncertainty perceived by an agent who observes and uses the survey forecasts to make its own probabilistic prediction.

A potentially major disadvantage of using the survey uncertainty measure, which could cause an unstable relationship with GDP growth, is the fact that the set of participating forecasters can change from one survey to the next. In addition to this, we do not know the specific forecasting models the forecasters have used. However, the survey uncertainty measure is relatively simple to calculate (precisely because one does not have to make one’s own forecast). Another concern is that the SPF provides density forecasts for only a few series, including real GDP growth since 1968, inflation since 1981 and, more recently, the unemployment rate. I use only the density forecasts for GDP growth to simplify our analysis, and because we hypothesize that expectations about GDP growth are among the most
important for consumer and firm behavior.

The rest of the paper is organized as follows. Section 2 defines the two measures of uncertainty used. Section 3 describes the data. In section 4, I conduct an experiment to determine whether the fluctuations in the survey uncertainty measure across time are primarily due to changes in forecaster composition or to “actual” changes in the risk faced by economic agents. Section 5 estimates relationships of the uncertainty measure with the values of real economic variables and compare the relationships to those between the same real economic variables and the uncertainty measures of LMN. In section 6, I look at the stability of both measures’ relationship with GDP growth across time. Section 7 concludes.

1.2 Definitions of uncertainty

JLN define uncertainty about a variable $y_j$, at time $t$, for an $h$-month-ahead forecast, as

$$U_{j,t,h} = \sqrt{E[(y_{j,t+h} - E(y_{j,t+h} | \xi_t))^2 | \xi_t]},$$

where $\xi_t$ is the information set used to make the forecast. Ludvigson, Ma and Ng (2016) then use the average of this expression across many financial variables $y_j$ to construct a measure of financial uncertainty:

$$FINU_{t,h} = \frac{1}{J} \sum_{j=1}^{N} U_{j,t,h}$$

for a panel $\{y_{j,s}\}_{j,s=1}^{J,T}$ of financial variables. The set of 147 financial variables includes valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads.

The other type of uncertainty measure considered in this paper is constructed from the density forecasts (for only GDP growth) of the SPF. As noted by Draper (1995), by the variance decomposition formula, given a set of $J$ models or structures for forecasting a variable $y$, the forecast variance of $y$ conditional on the collection of information sets $\mathcal{H} =$
\{S_j\} used in each of the structures is

$$V_f(y|\mathcal{S}) = \sum_{j=1}^{J} \pi_j \sigma_j^2 + \sum_{j=1}^{J} \pi_j (\mu_j - \bar{\mu})^2,$$

(1.1)

where

$$\bar{\mu} = \sum_{j=1}^{J} \mu_j,$$

$$\mu_j = E[y|S_j],$$

$$\sigma_j^2 = E[(y - \mu_j)^2|S_j],$$

and \{\pi_j\} are weights summing to 1 that indicate the amount of trust put in each structure.

Ideally we can identify individual forecasters in the SPF with structures, find the individual forecast mean and variance, and weight them by some function of the accuracy of their point forecasts. To start I simply give them equal weights. For comparison with LMN’s uncertainty measure, I work with the square root,

$$SD_f(y|\mathcal{S}) = \sqrt{V_f(y|\mathcal{S})}.$$

The first term in the expression for \(V_f\) is the conditional variance of the forecast error, averaged across forecasting models. The second term is the disagreement among forecasting models or structures. This expression has often been used alone as a proxy for uncertainty. Draper (1995) refers to this term as the between-structure variance, and to the first term as the within-structure variance. Including the within-structure variance in the measure arguably provides more information about uncertainty than disagreement alone, since disagreement uses only the mean forecast of each forecaster, ignoring the spread of their density forecasts. It turns out that the within-structure and between-structure variance move together to some extent (their contemporaneous correlation is 0.26 over the period 1968-2016), but this correlation does not seem to be enough to justify omitting one or the other.
The survey and LMN uncertainty measures have the same underlying definition of uncertainty, defining it as a forecast variance. Since

\[ V_f(y|\mathcal{I}) = E[(y - E(y|\mathcal{I}))^2|\mathcal{I}], \]

the basic expression for uncertainty about one variable in the Draper (1995) formulation looks the same as the corresponding expression in the JLN construction of uncertainty. The main difference is that while LMN form their forecasts conditional on a single (very large) information set, the survey uncertainty measure uses \( N_M \) potentially different information sets and combines them into one forecast variance. Apart from this, the only difference is that the LMN measure of uncertainty is an average of uncertainties for many economic variables, while the survey measure is based on only a single economic variable, GDP growth. This is because of the limited availability of density forecasts for other variables - the Survey of Professional Forecasters provides individual density forecasts only for GDP growth and inflation rates. Since uncertainty about GDP growth corresponds more closely to the type of uncertainty studied in the model in Paper 3 of this dissertation, I chose to use only the one variable, GDP growth.

### 1.3 Data

For the survey data, I take the GDP growth density forecasts from the Survey of Professional Forecasters, conducted by the NBER and American Statistical Association for 1968-1990 and by the Federal Reserve Bank of Philadelphia from 1990 on. The Survey of Professional Forecasters covers the period 1968Q4 to 2016Q4. The survey density forecasts are in the form of histograms. In each survey, the forecasters assign probabilities to the year-over-year GDP growth falling within different intervals, or bins, which include open intervals at either side. The endpoints of these bins change over time, depending on recent values of GDP growth. For instance, from 1973Q2 to 1974Q3, the upper endpoint of the second-to-highest
bin was 12, whereas from 1974Q4 to 1981Q2 it was 16, and from 1992Q1 to 2013Q4 it was 8. The forecasts are fixed-target: A survey is mailed out in January, April, July and October of each year, and forecasters make forecasts for that calendar year’s year-over-year GDP growth. Since at the 4th quarter (October) much of the growth for this year has been realized, the fourth-quarter forecasts are likely to be very accurate and not have much variance, whereas the first-quarter forecasts have much higher variance.

The data is in panel form. Individual forecasters are identified across surveys by an identification number. The composition of the surveys varies significantly, with many forecasters participating in only a few. Figure 1 shows the survey composition across surveys (x-axis), with one dot (y-axis) for each forecaster who participated in a survey.

![Figure 1.1: forecaster participation 1968-2016](image)

583 forecasters have participated at least once in the SPF. To be able to compare forecasters’ performance over time, I keep only forecasters who participated in 15 or more surveys. I also omit forecasts wherever probabilities do not sum to within (0.99, 1.01). This leaves a total of 174 forecasters, with an average of 35 surveys per forecaster and a maximum of 117. I define structures in the SPF as individual forecasters, find the individual forecast means and variances and weight them by some function of the accuracy of their forecasts as in equation
To start, forecasters are given equal weights. Then the weights are changed to a
decreasing function of a forecaster’s Brier score, a (decreasing) measure of density forecast
quality. The results found by using these two weighting schemes are very similar.

The determination of the individual forecast mean and variance requires some assumptions
about forecasters’ true subjective distribution. There is no information on how the forecaster
assigns probabilities to outcomes within a bin. If the true subjective forecast is single-peaked,
then the density is nondecreasing in the direction of the highest-probability bin. But there
is a possibility that sometimes forecasters have a multiple-peaked distribution. To try to
assume as little as possible about the distribution, I assign uniform densities within each
bin. Other authors have fitted normal or generalized-beta distributions to the histograms
(e.g. Engelberg, Manski and Williams 2011).

The individual mean for forecaster \( j \) is computed as

\[
\mu_j = \sum_{i=1}^{n} p_{i,j} x_i,
\]

where \( p_{i,j} \) is the probability forecaster \( j \) assigns to the \( i \)th bin, \( x_i \) is the midpoint of the \( i \)th
bin, and \( n \) is the number of bins. For the open-ended bins, I impose an endpoint such that
all bins have the same length, and take as \( x_i \) the midpoint of this new bin. Since forecasters
do not often assign much probability to the open-ended bins, this should not make much
difference in the results.

The individual variance for forecaster \( j \) is calculated as follows. Let \( b_1, \ldots, b_{n+1} \) be the end-
points of the bins (having replaced the open bins by closed ones). Denote by \( x \) the variable
being predicted (GDP growth). The variance equals \( \int_{b_i}^{b_{i+1}} (x - \bar{x})^2 dF(x) \), where \( F \) is the
cumulative distribution function for \( x \) and \( \bar{x} \) is the expected value of \( x \).

Let \( p_i \) be the probability a forecaster assigns to the bin \( [b_i, b_{i+1}] \). Then assuming uniform
distributions over each bin,

\[ dF(x) = \frac{p_i}{b_{i+1} - b_i}. \]

Then

\[ \int_{b_i}^{b_{i+1}} (x - \mu_j)^2 dF(x) = \int_{b_i}^{b_{i+1}} \frac{p_1(x - \mu_j)^2}{b_2 - b_1} dx + \cdots + \int_{b_n}^{b_{n+1}} \frac{p_n(x - \mu_j)^2}{b_{n+1} - b_n} dx. \]

Since

\[ \int_{b_i}^{b_{i+1}} \frac{p_i(x - \mu_j)^2}{b_{i+1} - b_i} dx = \frac{p_i}{b_{i+1} - b_i} \left( \frac{x^3 |_{b_i}^{b_{i+1}}}{3} - 2\mu_j \frac{x^2 |_{b_i}^{b_{i+1}}}{2} + \mu_j^2 (b_{i+1} - b_i) \right) \]

\[ = p_i \left( \frac{b_{i+1}^2 + b_i^2 + b_{i+1}b_i}{3} - \mu_j (b_{i+1} + b_i) + \mu_j^2 \right) \equiv p_i V_i, \]

the total variance equals

\[ \sigma_j^2 = \left( \begin{array}{cccc} p_1 & p_2 & \cdots & p_n \end{array} \right) \cdot \left( \begin{array}{cccc} V_1 & V_2 & \cdots & V_n \end{array} \right). \]

For the actual GDP growth rate, I use the seasonally adjusted real quarterly growth rates for 1968-2016.

The LMN financial uncertainty measure was obtained from Sydney Ludvigson’s website. I focus on the 3-month-ahead forecast uncertainty FINU3 for easier comparison with the quarterly survey uncertainty measure.

Figure 2 plots the average point forecasts together with true yearly GDP growth, which is what is being forecasted. Each point forecast is the average across the \( J \) mean forecasts \( \mu_j \) defined in equation (1.2).
Figure 1.2: One-quarter-ahead average forecasts and actual yearly GDP growth

Figure 1.2 shows that the point forecasts became quite a bit better starting around 1980. It could be that better forecasting methods began to be employed, or that the GDP growth series itself became more forecastable. To try to limit the possibility of extraneous factors influencing the survey measure, in the rest of this paper I focus on the period 1980-2016. Because of the short time span, I use quarterly data. Let $UC$ denote the survey uncertainty measure at horizon 1 (a one-quarter-ahead forecast). Figure 3 plots quarterly survey uncertainty together with financial uncertainty for 1980-2016.
The survey uncertainty measure is based on a fixed-target forecast. In each survey, forecasters make forecasts for the end-of-year GDP growth of that year, so there are four forecasts for each target. Since as the year passes, more information becomes available about how much GDP has already grown, uncertainty usually falls over the course of the year, unless something very unexpected occurs. To omit the forecast horizon effects, I run a regression of survey uncertainty on horizon dummies and a set of other economic variables including GDP growth, inflation and unemployment. These extra variables were chosen because their values are likely to affect the relationship between uncertainty and the forecast horizon. For instance, if inflation is unusually high, the uncertainty measure might not decrease as much as the horizon gets smaller as when inflation is normal (because forecasters presumably use current inflation in making their predictions of GDP growth and would tend to be more uncertain about where the economy is going when inflation is high). Then, if the regression omitted inflation, the coefficients on the horizon dummies would partly reflect the date-specific inflation rate instead of a more permanent effect of forecast horizon. Since I want to find the latter effect, I include economic variables considered important in making predictions of future GDP growth. Then I construct a new variable, denoted $UCH$, that subtracts the horizon dummy coefficient from survey uncertainty at each of the four horizons. A graph of this variable over time is shown in Figure 1.4.
By removing the horizon fixed effects, some of the variation in survey uncertainty that was due only to them disappears. The contemporaneous correlation between $UCH$ and $FINU3$ is 0.144 – still not very large, but larger than the correlation of 0.0950 between $UC$ and $FINU3$.

### 1.4 A test for the dependence of the survey uncertainty measure on survey composition

The set of forecasters participating in the SPF varies over time. Since forecasters may use different models and information sets to make predictions, survey composition could significantly affect the estimated relationships between survey uncertainty and other variables. This would make the measure less useful as a proxy for uncertainty. I therefore conduct a bootstrap test for the significance of survey composition in the relationship between survey uncertainty and GDP growth. The test is implemented by randomly drawing $n = 10$ of forecasters with replacement from those participating in each survey, computing the uncertainty measure for just those forecasters, and estimating the OLS coefficients in an OLS regression
of quarterly GDP growth on this uncertainty measure and other variables (federal funds rate, consumer price index, unemployment rate). The number 10 was chosen to ensure that there would be enough different possible forecaster compositions for each survey (i.e. that \( \binom{J}{n} \) is large enough for each \( s \), where \( J_s \) is the number of forecasters participating in survey \( s \)). The minimum number of forecasters in a survey is around 15, with 3003 possible subsets of size 10. I draw 2000 replications of forecaster sets for each survey. This results in a balanced panel with \( I = 2000 \) groups and \( T = 148 \) time periods.

The Lagrange-multiplier (LM) test statistic for constancy of coefficients is computed as in Breitung, Roling and Salish (2016). This method extends the Breusch and Pagan (1979) test to a panel data setting. For each bootstrapped sample \( i \), we have

\[
y_i = X_i \beta_i + \epsilon_i, \tag{1.3}
\]

\[
\epsilon_i \sim \mathcal{N}(0, \sigma^2), \tag{1.4}
\]

\[
\beta_i = \beta + v_i,
\]

\[
v_i \sim \mathcal{N}(0, \sigma_v^2),
\]

for \( i = 1, ..., I \), where \( y_i \) and \( \epsilon_i \) are \( T \times 1 \), \( \beta_i \) is \( k \times 1 \) and \( X_i \) is \( T \times k \). The null hypothesis is

\[
H_0 : \sigma_v = 0 \tag{1.5}
\]

and the alternative hypothesis is

\[
H_1 : \sigma_v > 0.
\]

In this application, \( y_i \) is GDP growth and \( X_i \) is the measure of forecast uncertainty constructed using the \( n \) forecasters selected for bootstrap sample \( i \).
For each bootstrapped sample \(i\), let \(u_i\) be the \(T\)-vector such that

\[
u_i = X_i v_i + \varepsilon_i,
\]

and let

\[
\hat{\sigma}^2 = \frac{1}{IT} \sum_{i=1}^I u_i' u_i.
\]

Under assumptions of normality and independence of the error vectors \(\varepsilon_i\) and \(v_i\), Breitung, Roling and Salish (2016) show that the LM test statistic for slope homogeneity is

\[
LM = s' V^{-1} s,
\]

where \(s\) is the \(k \times 1\) vector with \(r\)-th element

\[
s_r = \frac{1}{2\hat{\sigma}^4} \sum_{i=1}^I \left( \sum_{t=1}^T u_{i,t} x_{i,t,r} \right)^2 - \frac{1}{2\hat{\sigma}^2} \sum_{i=1}^I \sum_{t=1}^T x_{i,t,r}^2
\]

and \(V\) is the \(k \times k\) matrix with \((r,l)\) element

\[
V_{r,l} = \frac{1}{2\hat{\sigma}^4} \left[ \sum_{i=1}^I \left( \sum_{t=1}^T x_{i,t,r} x_{i,t,l} \right)^2 - \frac{1}{IT} \left( \sum_{i=1}^I \sum_{t=1}^T x_{i,t,r}^2 \right) \left( \sum_{i=1}^I \sum_{t=1}^T x_{i,t,l}^2 \right) \right].
\]

Breitung, Roling and Salish (2016) show that LM is asymptotically distributed \(\chi^2(k)\) as \(I \to \infty\) with \(T\) fixed, which is what we have. The experiments show that for low \(I\) (around 20), the null hypothesis is not rejected (\(LM \approx 5.5\)), but for large \(I\) (larger than 200) it is strongly rejected (\(LM \approx 2000\) when \(I = 3000\)). The LM statistic seems to diverge as \(I\) goes to infinity. I conclude that there is a significant amount of variation in the survey uncertainty measure due to composition effects. This may not invalidate the measure, though, if the effects are not economically significant. To see whether this is the case, I compute a one-period-ahead forecast of GDP growth in each of the replications based on the coefficient estimated in that replication. The box plots showing the distributions across replications of
the GDP growth forecasts for 1980-1999 and 2000-2016 are shown in Figure 1.5.

Figure 1.5: Box plots of one-quarter-ahead GDP forecasts, 1980-1988 (top) and 1990-1998 (bottom)

Note: Blue boxes represent the 25 – 75% interval across GDP forecasts made using uncertainty measured from different replications. Dashed lines represent the 5 – 95% interval. Red checks represent outliers.
Figure 1.6: Box plots of one-quarter-ahead GDP forecasts, 2000-2008 (top) and 2010-2016 (bottom)
In Figures 1.5 and 1.6 above, the 25 – 75% intervals make up less than one percentage point of GDP growth in most time periods. The 5 – 95% intervals are significantly larger, making up more than 2 percentage points of GDP growth in a few instances. Based on the 25 – 75% intervals, the composition of a survey is not likely to make much difference in its econometric impact on other variables. In the following section I study these impacts and compare them to those of LMN’s financial uncertainty measure.

1.5 Relationship with GDP growth

To compare the dynamic relationships between GDP growth and uncertainty measures, I run vector autoregressions with first survey uncertainty, then LMN’s financial uncertainty measure ($FINU3$) included as a dependent variable. The number of lags $s$ in each equation is determined by minimizing the Akaike information criterion, so it can be different depending on the uncertainty measure. The regression equation is

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \ldots + \Phi_s y_{t-s} + \eta_t,$$

where

$$y = \begin{pmatrix} GDPGR \\ UCH \\ FFR \\ UNEMP \\ CPI \end{pmatrix} \quad (1.10)$$
or

\[
\begin{pmatrix}
\text{GDPGR} \\
\text{FINU3} \\
\text{FFR} \\
\text{UNEMP} \\
\text{CPI}
\end{pmatrix}
\]

(1.11)

For both survey uncertainty (equation (1.10)) and financial uncertainty (equation (1.11)), the optimal number of lags is \( s = 2 \). The orthogonalized impulse responses of GDP growth to a shock to survey uncertainty and to a shock to financial uncertainty are graphed in Figure 1.7.

Figure 1.7: Orthogonalized impulse response of GDP growth to survey uncertainty (left) and to financial uncertainty (right)

The qualitative responses of GDP growth to shocks to the two types of uncertainty are quite different. The initial response to a one-standard-deviation shock to survey uncertainty is an increase of about 0.2 percentage points. The magnitude of the increase is slightly smaller than that of the initial decrease in response to a shock to financial uncertainty. After the initial increase, the response of GDP growth to survey uncertainty undershoots and returns to zero after around 12 quarters. The response to financial uncertainty overshoots, and returns to
zero after about 20 quarters. Overall, the impact of financial uncertainty on GDP growth is greater than that of survey uncertainty. The coefficient on the first lag of GDP growth in the survey uncertainty equation is negative, though not significant. This supports the idea that survey uncertainty is an outcome rather than a cause of lower growth. Recall that the SPF-based measure of uncertainty is based on forecasts of GDP growth. Ludvigson, Ma and Ng (2016) find that a shock to their real activity uncertainty measure, based on forecasts of real macroeconomic (as opposed to financial) variables increases GDP growth. They argue that this is consistent with growth options theories. The survey uncertainty measure differs from LMN’s real activity uncertainty measure in the kinds of forecasts used to construct it. The forecasters participating in the SPF have reported using intuition and simple autoregressive models in addition to structural models to make their forecasts. LMN use the same model to construct each forecast, and the model uses a large number of predictive variables, which are then projected onto a small set of regressors to make the forecast. Even if LMN use more information, they may use different information than the SPF participants, since LMN’s model does not change to account for qualitative factors such as political situations or changes in structural conditions of the economy that can be observed, but not really measured. The subjective nature of the SPF forecasts makes it possible for participants to incorporate such information into both their forecasts and their uncertainty. It is not clear how the sign and magnitude of the relationship between uncertainty and growth should change with the type of information is used to construct uncertainty. But we will see below that the shape of the orthogonalized impulse response graph of GDP growth to uncertainty changes less over time for survey uncertainty than for financial uncertainty. Possibly this is related to the way that the subjective survey uncertainty measure “adapts” to different conditions.


1.6 Tests for structural breaks

In this section I test for the stability of the relationship between the uncertainty measures and GDP growth across different time periods. This is done by performing a CUSUM test with unknown break for each uncertainty measure separately. The regression equations are

\[ \text{GDPGR}_t = \alpha + \beta_1 \text{GDPGR}_{t-1} + \beta_2 y_{t-1} + \beta_3 \text{FFR}_{t-1} + \beta_4 \text{UNEMP}_{t-1} \]

\[ + \beta_5 \text{CPI}_{t-1} + \eta_t, \]  \hspace{1cm} (1.12)

where \( y \) is successively equal to survey uncertainty and financial uncertainty. For survey uncertainty, a break was found at 2008Q4 with p-value 0.012. For financial uncertainty, a break was found at 1986Q3. This was just before the 1987 stock market crash, a time when financial uncertainty exhibits a spike, though there was no recession. Dividing the sample into post-1986 and pre-1986, I find that the post-1986 sample has a structural break at 2008Q4 with p-value 0.0007. Testing the survey uncertainty equation for a known structural break at 1986Q3, the null hypothesis of no structural break was rejected with a p-value of 0.0001.

To find out how the relationships of the uncertainty measures with GDP growth change over the sample periods, I divide the entire period into three sub-periods: 1980Q1-1986Q3 (27 observations), 1986Q4-2008Q4 (89 observations) and 2009Q1-2016Q4 (32 observations). I estimate VARs for each of the sub-periods, using equation (1.12). The coefficients on the uncertainty measures in the GDP growth equations for each of the sample periods are given in Table 1.
Table 1.1. Coefficient on uncertainty in GDP growth equation for OLS estimation of equations (1.12)

<table>
<thead>
<tr>
<th>Sample period</th>
<th>Lag</th>
<th>Coefficient (std dev)</th>
<th>Coefficient (std dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><strong>UCH</strong></td>
<td><strong>FINU3</strong></td>
</tr>
<tr>
<td>1980Q1-1986Q3</td>
<td>1</td>
<td>-1.60 (1.30)</td>
<td>-42.9*** (13.3)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-7.61*** (1.92)</td>
<td>48.9*** (14.8)</td>
</tr>
<tr>
<td>1986Q4-2008Q4</td>
<td>1</td>
<td>1.10 (2.22)</td>
<td>-2.41 (4.00)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-4.13* (2.12)</td>
<td>-2.49 (4.17)</td>
</tr>
<tr>
<td>2009Q1-2016Q4</td>
<td>1</td>
<td>2.30 (4.03)</td>
<td>14.7** (6.53)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>5.60* (3.30)</td>
<td>-7.60 (5.90)</td>
</tr>
</tbody>
</table>

The most striking observation in Table 1.1 is the change in sign of the coefficient on the first lag of financial uncertainty across time periods, from highly negative over 1980-1986Q3 to insignificantly negative in the period 1986Q4-2008 to significantly and highly positive in 2009-2016. The coefficient on the first lag of survey uncertainty also goes from negative to positive, but the change is of a smaller magnitude and the coefficient is never significant at the 10% level. The coefficient on the second lag of survey uncertainty is significantly negative in 1980-1986Q3, stays negative over 1986Q3-2008Q4 and becomes positive over the last period, always remaining significant at 10%.

The impulse-response graphs for impulse survey uncertainty (left column) and financial uncertainty (right column) for each of the three periods are shown in figures 1.8-1.10.
Figure 1.8: Orthogonalized impulse response of GDP growth to survey uncertainty (left) and to financial uncertainty (right) for the period 1980Q1-1986Q3

Figure 1.9: Orthogonalized impulse response of GDP growth to survey uncertainty (left) and to financial uncertainty (right) for the period 1986Q4-2008Q4
In the first row of the second column of Figure 1.8 (financial uncertainty in the early period), the impulse response of GDP growth bounces around, due to the very negative coefficient on one lag and high positive coefficient on the second lag of financial uncertainty. In the middle period the impact on GDP growth is smoother and overall much smaller. In the third period the initial impact is positive rather than negative, and the path looks like that of survey uncertainty. Of course the first and last periods considered are rather short, so any conclusions drawn from the impulse responses may be driven by specific events that occurred in those periods. The basic shape of the response of GDP growth to a shock to survey uncertainty stays the same across the periods, with an initial increase followed by a sharp decrease. One explanation for the patterns observed could be that changes in financial markets over the period 1980-2016 led both firms and consumers to change their response to financial uncertainty. By contrast, the survey uncertainty measure is based on the variance of forecasts for GDP growth. Possibly the response of GDP growth to this measure is more related to real behavior and less to financial considerations like speculation on the stock market or banks’ investment in risky assets.
1.7 Conclusions

This paper has studied two ways of measuring uncertainty – aggregating the subjective uncertainty from a survey of forecasters making forecasts for GDP growth, and constructing uncertainty from the variance of forecasts of financial variables using a very large data set (Ludvigson, Ma and Ng 2016, Jurado, Ludvigson and Ng 2015). The two measures are based on the same theoretical definition of uncertainty as the variance of a forecast, but differ in practice because the variables being forecast are different and the information sets and models used for forecasting may also be different. In all regressions of GDP growth on a set of economic variables, financial uncertainty has a large and significant coefficient. The coefficient on survey uncertainty is generally smaller in magnitude and less statistically significant. CUSUM tests revealed that both uncertainty series have structural breaks in their relationship with GDP growth at the same times: 1986Q3 and 2008Q4. Dividing the data into three periods delimited by those break dates, I find that the shape of the orthogonalized impulse function of financial uncertainty on GDP growth changes greatly over the periods, and the coefficient on financial uncertainty in the GDP growth equation of a VAR changes from very negative to positive. There is less change in the shape of the orthogonalized impulse response graph for survey uncertainty over the time periods.

1.8 Appendix - Unequal weights

In the main part of the text, I weighted all forecasters equally in computing the survey uncertainty measure. This section checks whether the results change when forecasters are given weights based on their previous forecast performance.

Suppose there are \( N_{tq} > 2 \) forecasters in the data. Given a survey \( s = (t, q) \), let

\[
\pi_s = (\pi_1, \ldots, \pi_{N_{tq}})
\]
be the weights assigned to forecasters \((1, \ldots, N_{tq})\) who participated in that survey. The uncertainty measure for that survey is

\[
U(\pi_s) = \sqrt{\sum_{n=1}^{N_{tq}} \pi_n (x_{n,s} - \bar{x}_s)^2 + \sum_{n=1}^{N_{tq}} \pi_n \sigma_{n,s}^2},
\]

where

\[
\bar{x}_s = \sum_{n=1}^{N_{tq}} \pi_n x_{n,s}
\]

is the weighted average of the forecasters’ mean forecasts and \(\sigma_{n,s}^2\) is forecaster \(n\)’s forecast variance for survey \(s\), whose computation is discussed above.

To find out whether the qualitative relationships between the uncertainty measure \(U(\pi_s)\) and real economic variables such as GDP growth are robust to the weights \(\pi_s\), I compute \(\{\pi_s\}\) so that the weight assigned to a forecaster in a given survey depends negatively on their average Brier score over all surveys they have participated in. The Brier score of a probabilistic forecast, where probabilities are assigned to a variable \(y\) falling within different intervals on the real line, is defined as

\[
bs = \sum_{r=1}^{R} (z_r - p_r)^2,
\]

where \(p_r\) is the probability assigned to the \(r\)th range (or bin) and \(z_r\) is one if the realized value of \(y\) falls within the \(r\)th range and zero otherwise. Denoting the (realized) GDP growth rate in year \(t\) by \(y_t\), for each forecaster \(n\), year \(t\) and quarter \(q\) I compute

\[
bs_{n,t,q} = \sum_{r=1}^{N_{tq}} (1\{y_t \in I_r\} - P_n(I_r))^2,
\]

where \(\{I_r\}_{r=1}^{R}\) are the intervals (some unbounded) to which the forecaster has assigned
probabilities \( P_n(I_r) \). Then let

\[
bs(n) = \frac{\sum \bs_{n,t,q} 1[n \text{ participated in survey}(t,q)]}{\sum (t,q) 1[n \text{ participated in survey}(t,q)]}
\] (1.15)

be the mean of the Brier scores for all the surveys forecaster \( n \) has participated in. Let \( \xi(n,t,q) \) equal one if forecaster \( n \) participated in survey \((t,q)\) and zero otherwise. A probabilistic forecast is better the lower its Brier score, so we work with the inverse (or another decreasing function) of the Brier score. For each survey \((t,q)\), find the sum of

\[
w_0(n) = (bs(n))^{-1}
\]

across all forecasters having participated, that is,

\[
W(t,q) = \sum_{n=1}^{N_{tq}} \xi(n,t,q)w_0(n).
\] (1.16)

Then define the weight on forecaster \( n \) in survey \((t,q)\) as

\[
\omega(n,t,q) = \frac{w_0(n)}{W(t,q)}.
\] (1.17)

Thus the weight assigned to a given forecaster can vary across surveys depending on which other forecasters have participated. If there are two surveys with identical forecaster composition, then the weights on each forecaster are identical across the two surveys. However, such a scenario does not occur often in this data (see figure 1). I denote the survey uncertainty measure with weights based on Brier scores as \( UC_{bs} \).

It turns out that this weighting scheme does not significantly affect the uncertainty measure. The correlation between the two measures is 0.947. I transform \( UC_{bs} \) in the same way as \( UC \), subtracting the coefficients on the horizon dummies in a regression of \( UC_{bs} \) in horizon dummies, GDP growth, consumer price index, federal funds rate and unemployment rate. The
transformed uncertainty measure is plotted in Figure 10 together with the equal-weighted uncertainty measure.

![Figure 1.11: Brier-weighted and equal-weighted uncertainty, horizon effects removed](image)

The qualitative results of this paper (not shown here) do not change when the Brier-weighted uncertainty measure is used instead of the one with equal weights.
Chapter 2

The Impact of Uncertainty on Job Creation and Destruction: How Much Do Entry and Exit Matter?

2.1 Introduction

Several theories have been proposed in the economic literature to explain the negative empirical relationship between uncertainty and growth. Theories that point to a causal effect of uncertainty on the business cycle generally involve frictions in some markets (Guglielminetti 2016). The frictions may prevent agents from completely insuring themselves against the consequences of high uncertainty. Basu and Bundick (2015) show that in a model with sticky prices and countercyclical price markups, the increase in precautionary saving caused by an exogenous increase in stock market volatility (VXO) leads to decreases in consumption, output, investment and hours worked, as seen in the data (Basu and Bundick 2015). Bloom (2009), Bloom et al. (2014) and Bachmann and Bayer (2013) consider the effects of uncertainty in models with real investment and hiring frictions. Other researchers have focused on the link between how firms react to changes in uncertainty and their suscepti-
bility to financial constraints or frictions. Gilchrist, Sim and Zakrajšek (2014) show that when the credit spread is included in a regression of growth on uncertainty, the coefficient on uncertainty becomes insignificant, whereas it was significant without the inclusion of credit spread. This points to financial frictions as a mechanism through which uncertainty influences output growth. Mecikovsky and Meier (2017) find that firms in industries more vulnerable to financial constraints have a significantly higher response to uncertainty shocks in terms of decreased job creation and increased job destruction.

This paper adds to the investigation into the relationships among uncertainty, financial variables and economic outcomes by studying empirically how uncertainty about financial conditions affects job creation and destruction by establishments at the intensive and extensive margins. I quantify the sensitivity of potential entrants and potential exitors to fluctuations in uncertainty about financial conditions, and compare it to that of continuing incumbents. For instance, if potential entering and exiting firms depend more on external finance, they may respond more strongly to uncertainty about its availability. The unit of measurement in this paper is an establishment rather than a firm, but a significant portion of establishments are also firms. 44.6% of employment consisted of employees in single-establishment firms in 2005. Using variance decomposition, I find that variance in the job creation rate by entrants accounts for 11 percent of the effect of an orthogonalized shock to financial uncertainty on the total variance of the quarterly job creation rate, and variance in the job destruction rate by exitors also accounts for about 11 percent of the effect on the variance of the job destruction rate.

Entry and exit of establishments seem like the types of decisions that could be strongly affected by the real-options effect (Dixit and Pindyck 1994, Bloom 2009). They are discrete decisions that generally entail large fixed and sunk costs. The real-options effect predicts that firms pause decisions such as exiting, hiring or firing during times of high uncertainty. However, the results of this paper show that the detrended job creation rate of entering establishments is not significantly related to the level of uncertainty. The job destruction
rate of exiting establishments moves in the opposite direction from what would be expected if agents were sensitive to the real-options effect, rising instead of falling in response to a shock to uncertainty.

I first look at the relationship between net job creation and uncertainty, then at the relationships between uncertainty and gross job creation and destruction. Finally I divide job creation into that by entering establishments and incumbents, and job destruction into that by incumbents and exiting establishments. Higher uncertainty has a negative effect on job creation and a positive effect on job destruction. The results for the decomposition of the effects of uncertainty on job creation and destruction show a greater dependence on the effects of uncertainty on actions taken by incumbents, rather than by entrants or exitors. I also estimate how much of the variability in GDP growth comes from the effects of uncertainty on job flows.

In interpreting these estimations, the negative correlation between uncertainty and the GDP growth rate has to be taken into account. This makes it necessary to separate the effects of higher uncertainty from those of lower GDP growth on hiring and firing. Another issue is that in the deep recession of 2009-2010, the measure of uncertainty studied in this paper – financial uncertainty – rose dramatically. This was probably because the recession is thought to have started with turmoil in financial markets. It is therefore important not to attribute the effects of a financial market crash or of lower GDP growth to uncertainty. I address the first issue by using a VAR estimation with uncertainty, job creation and destruction and GDP growth, where each variable’s previous values can affect each variable’s current value. The second issue is more difficult to address with the Bureau of Labor Statistics’ (BLS) Business Employment Statistics data set that I use, because the job creation and destruction data begins only in 1992. Theoretically one could estimate the regressions on different time intervals, excluding and including the period of the financial crisis, but the time series is probably too short for this. In future research I intend to compare the results found here with results found using the BLS’s Business Dynamics Statistics (BDS) database,
which has yearly data on firm characteristics starting in 1977.

The remainder of the paper is organized as follows. Section 2 describes the sources and construction of the data. Section 3 summarizes some of the properties of the data. In section 4, I conduct a vector autoregression analysis of the relationships among financial uncertainty and job destruction and creation, and section 5 concludes.

2.2 Data

The quarterly data on job creation and destruction come from the BDM dataset of the Bureau of Labor Statistics (BLS). The job creation rate is defined as the gross number of jobs created divided by the average of employment this period and employment last period. A job is considered to have been created (destroyed) if it was not (was) on the firm’s books in the third month of the previous quarter, and appears (does not appear) on the firm’s books in the third month of this quarter. Thus, these data do not count open positions that have not yet been filled. An entrant is defined as an establishment having positive employment in the third month of this quarter, but either no employment in the third month of the last quarter or no link to the last quarter. An exitor is defined as an establishment having either no positive employment this quarter or zero employment this quarter, when it had positive employment in the last quarter (Bureau of Labor Statistics website).

I use the uncertainty measure constructed by Jurado, Ludvigson and Ng (2015) and available on Sydney Ludvigson’s website. As Ludvigson, Ma and Ng (2016) find that their measure of financial uncertainty has more predictive power on GDP growth than their macro uncertainty measure, I focus on financial uncertainty as the main measure in this paper. Financial uncertainty at time $t$ regarding outcomes at time $t + h$ is defined as the average forecast variance over a set of economic variables $j = 1, ..., J$:

\[
FINU_{t,h} = \frac{1}{J} \sum_{j=1}^{J} U_{j,t,h},
\]  

(2.1)
with

\[ U_{j,t,h} = \sqrt{E[(y_{j,t+h} - E(y_{j,t+h} | \xi_t))^2 | \xi_t]}, \]

where \( \xi_t \) is the information set used to make the forecast. \( FINU \) is constructed using forecasts of \( J = 147 \) time series of financial variables including valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads, yields on corporate bonds of different ratings grades, yields on treasuries and yield spreads (Ludvigson, Ma and Ng 2016). I work with the one-month-ahead uncertainty measure \( FINU_1 \) because that is the one Ludvigson, Ma and Ng (2016) focus on in their study of the relationship between financial uncertainty and growth. However, the three- and twelve-month-ahead financial uncertainty are highly correlated with \( FINU_1 \), so the choice of \( FINU_1 \) as opposed to \( FINU_3 \) or \( FINU_{12} \) should not make much difference to the results.

### 2.3 Summary statistics

The abbreviations for the variables are as follows: \( FINU_1 \) is financial uncertainty based on one-month-ahead forecasts. \( GDPGR \) is the real quarter-to-quarter GDP growth rate, seasonally adjusted. \( JCR \) is the gross job creation rate, which equals the number of jobs created this quarter divided by average of this quarter’s and last quarter’s employment. \( JDR \) denotes the gross job destruction rate, calculated similarly. \( NJCR \) is the net job creation rate, equal to gross job creation rate minus gross job destruction rate. \( JCRE \) is the job creation rate by entrants and \( JCRI \) that by incumbents. \( JDREX \) is the job destruction rate by exitors and \( JDRI \) that by incumbents. The frequency of the job creation/destruction and GDP growth data series is quarterly. The frequency of the uncertainty series is monthly, but I average the values over every three months to make it quarterly, to be consistent with the other data.
I begin by separating the job creation rate and job destruction rate into trends and cyclical components. Both the job creation and job destruction rates have downward trends over the period 1993-2016, as can be seen in Figure 2.1. Most of the downward trend in the job creation rate is due to a downward trend in the job creation rate by incumbents as opposed to entrants, as shown in Figure 2.2.

![Figure 2.1: Job creation and destruction rates](image_url)
In the two recessions of the sample, in 2001 and 2008, the job creation rate by incumbents has a visible dip, which is reflected in the total job creation rate. No such dip is seen in the job creation rate by entrants. The number of entering establishments is known to be procyclical (e.g. Casares 2015), so for the job creation rate of entrants to stay nearly unchanged the average size of entering establishments would have to rise during recessions.
A similar fact is observed about the job destruction rate by exitors: Unlike the job destruction rate by incumbents, it does not have much of a visible upward hump at the two recessions. Since the number of exitors is countercyclical (though according to Lee and Mukoyama 2015 not as cyclical as entry for manufacturing plants), this would be consistent with the result that firms exiting during recessions tend to be smaller on average than those exiting during expansions.

The graph of the job creation by incumbents in Figure 2.1 shows a pronounced trend, decreasing by a total of about 1.3 percentage points from the late 1990’s to around 2010, then evening off at about 5.1% and recovering slightly after 2010. Figure 2.4 shows the HP-filtered series for job creation by incumbents.
Figure 2.4: Job creation rate by incumbents, HP-filtered

The trend for job creation by entrants declines over the entire period from the late 1990’s to 2016, though by less than the trend for incumbents, evening off only at the end of the period, as shown in Figure 2.5.
Figure 2.5: Job creation rate by entrants, HP-filtered

Figure 2.6 shows that the trends for job destruction by incumbents and by exitors similarly decline.
The long-term trends in the job creation rates by entrants and by incumbents are unlikely to be directly related to changes in uncertainty, as the uncertainty measures used in this paper display an almost constant trend. More probably, the decrease in the overall job creation rate has to do with changes in firm’s financing, together with the creation of new financial markets, or changes in the structure of firms, that are beyond the scope of this paper. The overall job destruction rate has experienced a downward trend of similar magnitude but larger than that of job creation, leaving the trend for net job creation decreasing on average over the sample period.
Figure 2.7: Net job creation rate

Figure 2.8: Trend net job creation rate
To measure relationships operating at different frequencies, I perform separate analyses using non-detrended data and using detrended series for the different types of job creation and destruction. Define $NJCR_{dt}$, $JCR_{dt}$ and $JDR_{dt}$ as the HP-detrended net job creation rate, gross job creation rate and gross job destruction rate. In Figure 10 one can see that the detrended gross job creation and job destruction rates are almost mirror images of each other during 2001 and 2009, while in most of the 1990’s and after 2012 their relationship is not so clear. I do not detrend the uncertainty series since it shows no significant trend. The contemporaneous cross-correlations among the detrended employment variables are given in Table 2.1.
Table 2.1. Contemporaneous correlations among job creation/destruction variables

<table>
<thead>
<tr>
<th></th>
<th>$JCR_{dt}$</th>
<th>$JCRE_{dt}$</th>
<th>$JCRI_{dt}$</th>
<th>$JDR_{dt}$</th>
<th>$JDREX_{dt}$</th>
<th>$JDRI_{dt}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$JCR_{dt}$</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$JCRE_{dt}$</td>
<td>0.6379</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$JCRI_{dt}$</td>
<td>0.9488</td>
<td>0.3620</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$JDR_{dt}$</td>
<td>-0.5234</td>
<td>0.0606</td>
<td>-0.6583</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$JDREX_{dt}$</td>
<td>-0.0171</td>
<td>0.4194</td>
<td>-0.1927</td>
<td>0.6525</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>$JDRI_{dt}$</td>
<td>-0.6065</td>
<td>-0.0542</td>
<td>-0.7119</td>
<td>0.9742</td>
<td>0.4644</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

The correlation between the detrended total job destruction and job creation rates is -0.52. By contrast, the correlation coefficient between non-detrended $JCR$ and $JDR$ is 0.37, and that between $JCRI$ and $JDRI$ it is 0.55, due to their shared downward trends. It is interesting that the correlation between the job creation rate of entrants and the job destruction rate of exitors remains positive at 0.42 after the trends have been taken out. Their correlation was almost 0.9 with the trends left in, so the downward trends in both were part of the reason for their high correlation.

2.4 VAR analysis

The goal of this section is to estimate the direct influence that financial uncertainty has on the job creation and destruction rates and the effect that financial uncertainty has on GDP growth through job creation and job destruction. Then I estimate the indirect effect of financial uncertainty on job creation and job destruction through its effect on entrants and exitors respectively.

Since each of the variables - the job creation rates, job destruction rates, uncertainty and GDP growth - may have a causal effect on each of the others, and this most likely occurs with some lag, it makes sense to use vector autoregression to try to untangle the relationships among them. I use the Aikaike information criterion to choose the number of lags for each
equation.

The VAR equations used are of the form

\[ y_t = \Phi_0 + \Phi_1 y_{t-1} + \ldots + \Phi_p y_{t-p} + \varepsilon_t, \]

with

\[ \varepsilon_t \sim \mathcal{N}(0_n, \Omega), \] (2.2)

where \( n \) is the size of \( y \). I use several specifications, considering first

\[ y = \begin{pmatrix} FINU1 \\ GDPGR \\ JCR \\ JDR \end{pmatrix}, \] (2.3)

and next the same equation with job creation and destruction replaced by their detrended counterparts:

\[ y = \begin{pmatrix} FINU1 \\ GDPGR \\ JCR_{dt} \\ JDR_{dt} \end{pmatrix}. \] (2.4)

Among specifications with 1 to 6 lags, the criterion is minimized at 4 lags for both the detrended and non-detrended equations. For equation (2.3), Figure 2.10 shows orthogonlized impulse responses of job creation and destruction rates to financial uncertainty and of GDP growth to job creation and destruction rates (job creation/destuction rates are not detrended).
In Figure 2.10, a one-standard-deviation shock to financial uncertainty has a relatively small but persistent impact on the job creation rate. The peak impact is -0.08 percentage points at around 3 quarters after the shock, but the job creation rate does not recover until after 20 quarters. For the job destruction rate, the impact of a financial uncertainty shock is to first increase it. The job destruction rate then falls, becoming negative at around quarter 8. It does not return to zero within 20 quarters. The persistence of the shock to job creation suggests that financial uncertainty could prolong a recession through the channel of lower job creation. However, the orthogonalized impulse response of the detrended job creation rate to financial uncertainty, shown below, is much less persistent. This could imply that the apparent persistence in the response of the job creation rate with the trend is due to some of the actual downward trend in job creation being wrongly attributed to the shock. The persistence of the undershooting of the job destruction rate with trend can similarly be attributed to its downward trend. It therefore seems more useful to consider the detrended job creation rate if the short-term effects of financial uncertainty are being studied.

Figure 2.11 contains the counterpart to Figure 2.10 with detrended job creation and destruction rates. In the left panel of Figure 2.11, the peak impact of financial uncertainty on
detrended job creation, at around -0.06, is less in absolute value than that for job creation with the trend. It also recovers much faster, reaching zero at approximately 8 quarters after the shock, and staying near zero for the rest of the period. In the right panel, the response of the job destruction rate first rises to almost 0.1 at quarter 3, then slightly undershoots starting at quarter 7 and returns to zero by quarter 18. In the regression with detrended job creation and destruction, the responses of these variables are much less persistent than for their non-detrended counterparts. The response of detrended job destruction is larger in magnitude than that of detrended job creation. Also, the response of detrended job destruction stays slightly negative for some time after undershoot before returning to zero.

![Graphs showing impulse responses](image)

Figure 2.11: Orthogonalized impulse responses, financial uncertainty on detrended job creation rate (left) and on detrended job destruction rate (right)

Next the job creation and destruction rates are split into their components at the intensive and extensive margins. I use combinations of the AIC, the Hannan-Quinn information criterion (HQIC), the Schwarz Bayesian information criterion (SBIC) and the final prediction error (FPE) in choosing the number of lags in these VARs. For the equation with non-detrended job creation and destruction rates, both the AIC and FPE choose four lags as optimal among 1-6 lags, while the HQIC and SBIC choose two and one lags, respectively.
I choose to implement the estimation with four lags. For the equation with detrended job creation/destruction rates, the FPE, HQIC and SBIC indicate that one lag is optimal, while according to the AIC it is four lags. I choose one lag for this equation. The left column of Table 2.2 shows the VAR coefficients on the four lags of $FINU1$ in each of the non-detrended job creation/destruction equations, for the regression with

$$
y = \begin{pmatrix}
FINU1 \\
GDPGR \\
JCRE \\
JCRI \\
JDREX \\
JDRI
\end{pmatrix}.
$$

(2.5)

The right column of Table 2.2 shows the coefficients on one lag of $FINU1$ for the detrended job creation/destruction rates in the regression equation

$$
y = \begin{pmatrix}
FINU1 \\
GDPGR \\
JCRE_{dt} \\
JCRI_{dt} \\
JDREX_{dt} \\
JDRI_{dt}
\end{pmatrix}.
$$

(2.6)

Table 2.2. VAR coefficients on lags of $FINU1$ for job creation/destruction equations from equations (2.5) and (2.6)
<table>
<thead>
<tr>
<th>Variable</th>
<th>Lag</th>
<th>Coefficient (std.dev.)</th>
<th>Variable</th>
<th>Lag</th>
<th>Coefficient (std.dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td>JCRE</td>
<td>1</td>
<td>-0.342*** (0.123)</td>
<td>JCRE&lt;sub&gt;dt&lt;/sub&gt;</td>
<td>1</td>
<td>-0.0254 (0.0460)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.374* (0.206)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-0.196 (0.206)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>-0.0838 (0.134)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JCRI</td>
<td>1</td>
<td>-0.505* (0.275)</td>
<td>JCRI&lt;sub&gt;dt&lt;/sub&gt;</td>
<td>1</td>
<td>-0.123 (0.0879)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.462 (0.463)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-0.599 (0.462)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.530* (0.300)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JDREX</td>
<td>1</td>
<td>0.0917 (0.112)</td>
<td>JDREX&lt;sub&gt;dt&lt;/sub&gt;</td>
<td>1</td>
<td>0.0855** (0.0402)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.0292 (0.189)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.0312 (0.188)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>-0.0555 (0.122)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JDRI</td>
<td>1</td>
<td>0.812*** (0.265)</td>
<td>JDRI&lt;sub&gt;dt&lt;/sub&gt;</td>
<td>1</td>
<td>0.180** (0.0899)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-0.298 (0.446)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-0.174 (0.445)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>-0.392 (0.289)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**NOTE:** One star denotes significance at the 10% level, two stars at the 5% level and three stars at the 1% level.

The right side of Table 2.2 shows that of the detrended job creation/destruction variables, only job destruction by exitors and incumbents have coefficients on financial uncertainty that are significant at the 5% level. In the \( JDRI_{dt} \) equation, the coefficient on the first lag of \( FINU_1 \) is 0.18, meaning that a one-unit increase in \( FINU_1 \) is associated with a 0.18 percentage-point increase in the detrended job destruction rate by incumbents. While \( FINU_1 \) ranges only from 0.65 to 1.49, \( JDRI_{dt} \) ranges only from -0.416 to 1.15, so that a change from the lowest to the highest value of financial uncertainty could be expected to lead to a moderately important change in the detrended part of \( JDRI \). The relationship between \( FINU_1 \) and the detrended job destruction rate of exitors is weaker, with a coefficient of 0.0855. For the detrended job creation rates by entrants and incumbents, the coefficients on lagged \( FINU_1 \) are negative as would be expected from the option value theory. However, neither is significant at the 10% level.

On the left side of Table 2.2, three variables - the job destruction and job creation rates by
incumbents and the job creation rate by entrants - have coefficients on one lag of financial uncertainty that are significant at the 5% level. These coefficients are large in magnitude, implying that a one-unit increase in last quarter’s financial uncertainty is associated with one-third and one-half percentage point decreases in $JCRE$ and $JCRI$ respectively, and with a 0.8 percentage point increase in $JDRI$. By contrast, none of the coefficients on financial uncertainty in the job destruction rate by exitors equation is significant at 5%, and the coefficient on one lag of financial uncertainty is less than 0.1. The situation is very different on the right side of Table 2.2. Here the coefficients on $FINU_1$ in both detrended job destruction equations are significant at 5% and the coefficients in both detrended job creation equations are highly insignificant. To avoid interference from the downward trends in all the job creation/destruction variables, in the following explanation of the results I focus on equation (2.6).

The coefficients in the right-hand side of Table 2.2 seem at odds with the findings of authors such as MacNamara (2014) and Mecikovsky and Meier (2017) that financial variables are especially important for entering firms. If the financial variables whose forecast uncertainty is rising are important for the entry decisions of potential entrants and for the hiring decisions of beginning firms, then one would think that uncertainty about them might lead such firms to be more cautious and enter with fewer employees. It bears noting that the unit of measurement here is an establishment rather than a firm, but a significant portion of entering establishments are also firms. For instance, of the establishments entering in the year 2004 with less than 50 employees, 97% were also firms. For entering establishments of all size classes, 77% were also firms in 2004. If in fact the entry and initial size decisions of start-ups are relatively unaffected by financial uncertainty, it could be that the first moment of these financial variables matters, though uncertainty about it does not. Several studies suggest that entrepreneurs are more optimistic and less risk-averse than the general population (e.g. Baumol 2010). If the entrepreneur continues to exercise control over the company and continues to be optimistic, then incumbents would also be little affected by uncertainty.
The rise in job destruction by incumbents is consistent with the real-options theory discussed in Dixit and Pindyck (1994). Since a job is counted as destroyed if it had been on the firm’s books last quarter but is no longer there, firms could be simply not replacing those workers who quit. As Bloom et al. (2014) mention, the lack of replacement of quitting workers during periods of high uncertainty leads to a net decrease in employment in their model, since there is no change in the rate of attrition as uncertainty rises. However, the rise in job destruction by exiting establishments most likely means that more firms are exiting as well. The real-options theory predicts that given a fixed level of GDP growth, firms would tend to stay in the market longer when uncertainty rises, waiting for more information to make a costly and irreversible exit. Figure 2.12 illustrates the differences in response of the non-detrended and detrended job creation rates by entrants to a shock to financial uncertainty, and Figure 2.13 shows the responses of the non-detrended and detrended job destruction rates by exitors.

![Graph 1](image1.png) ![Graph 2](image2.png)

Figure 2.12: Orthogonalized impulse responses, financial uncertainty on non-detrended job creation rate by entrants (left) and on detrended job creation rate by entrants (right)
Figure 2.13: Orthogonalized impulse responses, financial uncertainty on non-detrended job destruction rate of exitors (left) and on detrended job destruction rate of exitors (right)

### 2.4.1 Variance decomposition

The first aim of this section is to determine what portion of the variation in each of $JCR_{dt}$, $JCRI_{dt}$, $JCRE_{dt}$, $JDR_{dt}$, $JDREX_{dt}$ and $JDRI_{dt}$ is due to variation in $FINU1$. Then I extend the process of variance decomposition to find the portion of the variation in $JCR_{dt}$ due to $FINU$ through its action on $JCRE_{dt}$ (versus the portion due to its action on $JCRI_{dt}$). Similarly, I find the portion of the variation in $JDR_{dt}$ due to $FINU$ through its action on $JDREX_{dt}$, as opposed to its action on $JDRI_{dt}$. The purpose of this exercise is to find out not only which types of job creation and destruction are most affected by financial uncertainty, but also which end up having the most effect on overall fluctuations in job creation and destruction. This question could be of interest to policymakers trying to dampen fluctuations due to uncertainty.

The portion of variance in each of $JCR_{dt}$ and $JDR_{dt}$ due to $FINU1$ within the specification of equation (3.3) is found by standard variance decomposition. The results are presented in Table 2.3.

Table 2.3. Variance decomposition with impulse financial uncertainty
<table>
<thead>
<tr>
<th>Variable</th>
<th>Portion of Variance</th>
<th>Portion of Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 quarters ahead</td>
<td>20 quarters ahead</td>
</tr>
<tr>
<td>FINU1</td>
<td>0.991</td>
<td>0.967</td>
</tr>
<tr>
<td>GDPGR</td>
<td>0.146</td>
<td>0.146</td>
</tr>
<tr>
<td>JCR&lt;sub&gt;dt&lt;/sub&gt;</td>
<td>0.142</td>
<td>0.150</td>
</tr>
<tr>
<td>JDR&lt;sub&gt;dt&lt;/sub&gt;</td>
<td>0.289</td>
<td>0.287</td>
</tr>
</tbody>
</table>

Portion due to shocks to GDPGR

<table>
<thead>
<tr>
<th>Variable</th>
<th>Portion of Variance</th>
<th>Portion of Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 quarters ahead</td>
<td>20 quarters ahead</td>
</tr>
<tr>
<td>FINU1</td>
<td>0.00161</td>
<td>0.00460</td>
</tr>
<tr>
<td>GDPGR</td>
<td>0.784</td>
<td>0.778</td>
</tr>
<tr>
<td>JCR&lt;sub&gt;dt&lt;/sub&gt;</td>
<td>0.0668</td>
<td>0.0668</td>
</tr>
<tr>
<td>JDR&lt;sub&gt;dt&lt;/sub&gt;</td>
<td>0.132</td>
<td>0.131</td>
</tr>
</tbody>
</table>

A shock to financial uncertainty generates almost all of the MSE of a 5- and 20- period-ahead forecasts for financial uncertainty. For the job destruction rate, it generates between one-quarter and one-third of the 5- and 20- period-ahead MSE, and for the job creation rate, it contributes between one-eighth and one-sixth. The larger contribution of financial uncertainty shocks to the variance of the job destruction rate, compared to that of the job creation rate, matches with the results from the orthogonalized impulse response function (Figure 2.11) for equation (2.4), which shows an association of financial uncertainty with job destruction that is more significant and larger in magnitude than the association with job creation. By way of comparison, the contribution of GDPGR to the 20-period-ahead MSE of JCR<sub>dt</sub> is 0.0668 and the contribution to the 20-period-ahead MSE of JDR<sub>dt</sub> is 0.131. This seems to suggest that fluctuations in financial uncertainty are more important than fluctuations in GDP growth for generating variation in the detrended measures of job creation and destruction. The tiny portion of fluctuation in financial uncertainty attributable to the shock to GDP growth is surprising, but in line with the results of Ludvigson, Ma and
Ng (2016) which lead them to conclude that financial uncertainty is an exogenous cause of economic downturns.

Next I divide detrended job creation into $JCRE_{dt}$ and $JCRI_{dt}$, and detrended job destruction into $JDREX_{dt}$ and $JDRI_{dt}$, and perform variance decomposition of the effects of $FINU1$ on the job creation/destruction rates by entrants, incumbents and exitors.

Table 2.4. Variance decomposition with impulse financial uncertainty, equation (3.5)

<table>
<thead>
<tr>
<th>Variable</th>
<th>5 quarters ahead</th>
<th>20 quarters ahead</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Portion of Variance</td>
<td>Portion of Variance</td>
</tr>
<tr>
<td>$FINU1$</td>
<td>0.944</td>
<td>0.898</td>
</tr>
<tr>
<td>$GDPGR$</td>
<td>0.0886</td>
<td>0.122</td>
</tr>
<tr>
<td>$JCRE_{dt}$</td>
<td>0.0263</td>
<td>0.0270</td>
</tr>
<tr>
<td>$JCRI_{dt}$</td>
<td>0.110</td>
<td>0.171</td>
</tr>
<tr>
<td>$JDREX_{dt}$</td>
<td>0.0803</td>
<td>0.134</td>
</tr>
<tr>
<td>$JDRI_{dt}$</td>
<td>0.192</td>
<td>0.274</td>
</tr>
</tbody>
</table>

Portion due to shocks to $GDPGR$

<table>
<thead>
<tr>
<th>Variable</th>
<th>5 quarters ahead</th>
<th>20 quarters ahead</th>
</tr>
</thead>
<tbody>
<tr>
<td>$FINU1$</td>
<td>0.0128</td>
<td>0.0334</td>
</tr>
<tr>
<td>$GDPGR$</td>
<td>0.845</td>
<td>0.812</td>
</tr>
<tr>
<td>$JCRE_{dt}$</td>
<td>0.0477</td>
<td>0.0477</td>
</tr>
<tr>
<td>$JCRI_{dt}$</td>
<td>0.142</td>
<td>0.135</td>
</tr>
<tr>
<td>$JDREX_{dt}$</td>
<td>0.0213</td>
<td>0.0222</td>
</tr>
<tr>
<td>$JDRI_{dt}$</td>
<td>0.258</td>
<td>0.233</td>
</tr>
</tbody>
</table>

In this estimation, innovations to financial uncertainty play a very small role (< 3%) in predicting variation in the detrended job creation rate by entrants. Financial uncertainty is much more important in predicting variation in the job creation rate by incumbents, contributing around one-tenth of the five-step-ahead MSE and more than one-sixth of the
20-step ahead MSE. Similarly, an innovation to financial uncertainty contributes more than one-fourth of the MSE of the job destruction rate by incumbents, and about one-tenth of the job destruction rate by exitors. These results reinforce the hypotheses stated above that job destruction is more sensitive to variations in uncertainty than job creation, and that the intensive margins of job creation and destruction (incumbent establishments) are more sensitive to variations in uncertainty than the extensive margins (entrants and exitors). The larger contribution to the variance of the job destruction rates, compared to that of the job creation rates, matches with the results from the VAR (equation (2.6)), which show an association of financial uncertainty with job destruction that is more significant and larger in magnitude than the association with job creation.

2.4.2 Decomposition of variance decomposition

In this subsection, I conduct an exercise designed to answer the following questions:

1. How important is the channel of job creation by entrants in estimating the effect of uncertainty on job creation?

2. How important is the channel of job destruction by exitors in estimating the effect of uncertainty on job destruction?

3. How important are the channels of job creation and destruction in estimating the effect of uncertainty on GDP growth?

The third question is based on the observation by MacNamara (2014) and other authors that job creation and destruction lead the business cycle.

To answer questions 1 and 2, I find the relative contributions of the job creation rates of incumbents and of entrants to the 20-quarter-ahead MSE of the total job creation rate, and the contributions of the job destruction rates of incumbents and exitors on the 20-quarter-ahead MSE of the total job destruction rate. For this I use the specifications
\[ y = \begin{pmatrix} FINU1 \\ GDPGR \\ JCRE \\ JCRI \\ JDREX \\ JDRI \end{pmatrix} \] 

(2.7)

and

\[ y = \begin{pmatrix} FINU1 \\ GDPGR \\ JCRE_{dt} \\ JCRI_{dt} \\ JDREX_{dt} \\ JDRI_{dt} \end{pmatrix} \]

(2.8)

Again, \( y \) follows a VAR(\( p \)) process,

\[ y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-p} + \varepsilon_t, \]

with \( p = 4 \) for the non-detrended specification and \( p = 1 \) for the detrended one.

Let

\[ \Pi = \begin{pmatrix} c' \\ \Phi_1' \\ \vdots \\ \Phi_p' \end{pmatrix} \]

Since \( y_t \) is covariance-stationary in all the cases considered here, it can be written in MA(\( \infty \)) form as

\[ y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \ldots. \]
Then $\Phi_j$ and $\Omega$ can be estimated by OLS: Let

$$\hat{\Pi}' = \left[ \sum_{t=1}^{T} y_t x'_t \right] \left[ \sum_{t=1}^{T} x_t x'_t \right]^{-1},$$

where

$$x_t = \begin{pmatrix} 1 \\ y_{t-1} \\ \vdots \\ y_{t-p} \end{pmatrix}$$

and $T + p$ is the number of observations. $\hat{\Phi}_j$ is obtained from $\hat{\Pi}$ by extracting the $(j + 1)$th submatrix in the horizontal direction of $\hat{\Pi}'$ (since the first submatrix corresponds to the constant $c$).

The estimated error terms are

$$\hat{\varepsilon}_t = y_t - \hat{\Pi}' x_t.$$

The variance of the errors is estimated by

$$\hat{\Omega} = \frac{1}{T} \left( \sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}'_t \right).$$

Then the $\{\hat{\Psi}_j\}_{j=1}^{S}$ are found by simulating the VAR($p$) with the OLS coefficients, setting the appropriate error terms to zero.

$\hat{\Omega}$ can be decomposed as

$$\hat{\Omega} = \hat{A} \hat{A}',$$

where $\hat{A}$ is the Choleski decomposition of $\hat{\Omega}$. As stated in Hamilton (1994), p.324, the contribution of a one-standard-deviation orthogonalized innovation to $FINU1$ to the mean-
squared error (MSE) of the $s$- period ahead forecast of $JCR$ can be estimated as

$$\hat{M} = \hat{a}_1 \hat{a}_1' + \hat{\Psi}_1 \hat{a}_1 \hat{a}_1' \hat{\Psi}_1' + ... + \hat{\Psi}_{s-1} \hat{a}_1 \hat{a}_1' \hat{\Psi}_{s-1}',$$

(2.9)

where $\hat{a}_j$ is the $j$th column of $\hat{A}$.

Since the non-detrended variables $JCRE$ and $JCRI$ sum to $JCR$ and similarly for $JDREX$, $JDRI$ and $JDR$, and the detrending of all variables applies the same smoothing parameter, the detrended parameters have nearly the same relationships. Therefore, one can decompose the effect of a shock to $FINU1$ on the total variance of $JCR_{dt}$ into the sum of the effects of a shock to $FINU1$ on the variance of $JCRE_{dt}$, on the variance of $JCRI_{dt}$ and on two times the covariance of $JCR_{dt}$ and $JCR_{dt}$. The goal is to find the portion of this contribution that is coming through the effect of $FINU$ on $JCRE$. Since

$$Var(JCR) = Var(JCRE) + Var(JCRI) + 2Cov(JCRE, JCRI)$$

(2.10)

the contribution of an innovation to $FINU1$ to the variance of the job creation rate can be similarly decomposed. I calculate the contribution of financial uncertainty to each of the right-hand-side components in equation (3.9), then divide by the total contribution of $FINU1$ to the variance of $JCR$.

Specifically, let

$$z = \begin{pmatrix} FINU1 \\ GDPGR \\ JCR \\ JDREX \\ JDRI \end{pmatrix},$$

55
and let

\[
y = \begin{pmatrix}
FINU1 \\
GDPGR \\
JCRE \\
JCR1 \\
JDREX \\
JDR1
\end{pmatrix}.
\]

Let

\[
H = \begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}.
\]

Then

\[
z = Hy,
\]

and so

\[
MSE(\hat{z}_{t+s|t}) = H\{MSE(\hat{y}_{t+s|t})\}H'
\]

\[
= H \sum_{j=1}^{6} [\hat{a}_j \hat{a}'_j + \Psi_1 \hat{a}_j \hat{a}'_j \Psi_1' + ... + \Psi_{s-1} \hat{a}_j \hat{a}'_j \Psi_{s-1}']H'.
\]

I am interested in the (3,3) element of \(MSE(\hat{z}_{t+s|t})\), which is the MSE of the total job creation rate, and how it relates to an orthogonalized shock to financial uncertainty. The (3,3) element of \(H\hat{a}_1 \hat{a}'_1 H'\) is

\[
(a_{3,1} + a_{4,1})^2,
\]

where \(a_{i,j}\) is the \(i\)th element of \(\hat{A}\). So the (3,3) element of \(H\hat{a}_1 \hat{a}'_1 H'\) is the (3,3) element of \(\hat{a}_1 \hat{a}'_1\) plus the (4,4) element of \(\hat{a}_1 \hat{a}'_1\) plus two times the (3,4) element of \(\hat{a}_1 \hat{a}'_1\). The same kind of decomposition can be performed for the \(\Psi_r \hat{a}_1 \hat{a}'_1 \Psi_r\) terms of the expression for \(MSE(\hat{z}_{t+s|t})\).
for $r = 1, \ldots, s - 1$ to show that the $(3,3)$ element of $MSE(\hat{z}_{t+s|t})$ is equal to the $(3,3)$ element of $MSE(\hat{y}_{t+s|t})$ plus its (4,4) element plus two times its (3,4) element. To find the portion of the variance of the $s$-period-ahead forecast for the job creation rate due to financial uncertainty that comes through the job creation rate of entrants, I take

$$\frac{MSE(\hat{y}_{t+s|t})(3,3)}{MSE(\hat{z}_{t+s|t})(3,3)}.$$ 

For the detrended variables, the contribution of job creation by entrants to the total contribution of a shock to financial uncertainty to the $s$-period-ahead mean squared error of the job creation rate converges to 4.35% as $s$ gets large. For the variables with trend, the number is 10.98%. The same procedure was performed for the job destruction rate by exits, resulting in 1.9% for the detrended variables and 11.10% for the ones with the trend left in. By contrast, the contribution of the effect of financial uncertainty on the job creation of incumbents to the entire job creation rate is about 77% without the trend and 45% with the trend. For job destruction, the contribution of the effect of incumbents is 76% without the trend and 44% with the trend. The remainder of the contribution comes from the effect of financial uncertainty on the covariance between the job creation/destruction rate by entrants/exitors and the job creation/destruction rate by incumbents.

To answer the third question, I start with the estimated VARs for equations (2.3) and (2.4), that is,

$$y = \begin{pmatrix} FINU1 \\ GDPGR \\ JCR \\ JDR \end{pmatrix}.$$
and

\[
y = \begin{pmatrix}
  FINU1 \\
  GDPGR \\
  JCR_{dt} \\
  JDR_{dt}
\end{pmatrix},
\]

using four lags for each of the regressions as above.

To find the portion of this contribution that is coming through the effect of FINU1 on JCR, I use the same method as for answering questions 1 and 2, shutting down the effects of FINU1 on GDPGR that are coming through other channels besides the effect of FINU1 on JCR. As above, let

\[
\hat{\Omega} = E[\varepsilon_t' \varepsilon_t]
\]

be the error variance of the autoregressive equation estimated by OLS, and let \(\hat{A}\) be the Choleski decomposition of \(\hat{\Omega}\). Let \(\hat{a}_1\) be the first column of \(\hat{A}\) and create \(\hat{\alpha}_1\) by replacing the first, second and fourth elements of \(\hat{a}_1\) by zero. Then find

\[
\hat{M}_0 = \hat{\alpha}_1' \hat{\alpha}_1' + \Psi_1 \hat{\alpha}_1' \Psi_1' + \ldots + \Psi_{s-1} \hat{\alpha}_1' \Psi_{s-1}'
\]

and take

\[
\hat{M}_1(i,j) = \frac{\hat{M}_0(i,j)}{\hat{M}(i,j)}
\]

for \(i, j = 1, \ldots, p\). The effect of a one-standard-deviation orthogonalized shock to FINU1 on GDP growth through JCR is the (2,2) element of the matrix \(\hat{M}_0\). The portion of the total effect on GDPGR is the (2,2) element of \(\hat{M}_1\). For the 20-quarter-ahead MSE of GDP growth, this is only 0.004% for the non-detrended job creation rate and 0.18% for the detrended job creation rate. These results suggest that a lower job creation rate is not a channel through which financial uncertainty affects GDP growth. For the non-detrended job destruction and detrended job destruction rates, the numbers are 0.64% and 1.9% respectively. So none of
the job creation or destruction channels contribute much to the effect of financial uncertainty on GDP growth.

2.5 Discussion and conclusions

This paper has studied the differential effects of Ludvigson, Ma and Ng’s (2016) financial uncertainty measure on the job creation rates of incumbents and entering establishments and on the job destruction rates of incumbents and exiting establishments. I have used this measure because Ludvigson, Ma and Ng (2016) found it to have a causal effect on real variables in the economy, while a measure of real activity uncertainty they constructed did not. Since my goal was to find a channel of potential causality, I needed to start with a measure of uncertainty that had some causal effect on the economy.

In the period 1993-2016, financial uncertainty had a more significant and larger-in-magnitude negative effect on the job creation rate of incumbents than of entrants, and a more significant positive effect on the job destruction rate of incumbents than of exitors. For detrended creation and destruction, financial uncertainty had a more significant and stronger effect on the job destruction rates by incumbents and exitors than on the job creation rates by incumbents and entrants. About 11% of variation in the job creation rate due to a shock to financial uncertainty came through the channel of job creation by entrants, and about 11% of variation in the job destruction rate due to a shock to financial uncertainty came through the channel of job destruction by exitors. For their detrended counterparts, these numbers are only 5% and 2%. Compared to the proportion of jobs created due to entry of establishments and the proportion of jobs lost due to exit of establishments – both averaging about 20% over the sample period – the variance decomposition numbers are quite small.

The direction of the responses of the total job creation and job destruction rates to a rise in financial uncertainty are consistent with the interactions of uncertainty with financial frictions (Mecikovsky and Meier 2017). Sticky prices (Basu and Bundick 2014) also lead to
a decrease in job creation and increase in job destruction as a result of a rise in uncertainty: Due to asymmetry in the profit as a function of price, higher uncertainty causes firms to increase their price, produce less output, and therefore hire fewer and fire more workers. Labor-adjustment frictions would tend to decrease both job creation and job destruction through the real-options effect, and capital-adjustment frictions would also decrease both creation and destruction through the complementarity of capital and labor. In an industry-level study of the responses of gross job creation and destruction to uncertainty, Mecikovsky and Meier (2017) find little relationship between the level of price rigidity in an industry and the reaction of job flows to uncertainty, and little effect of the level of capital frictions in an industry on the response of job creation to uncertainty. In contrast, they find a significant effect of the severity of financial frictions in an industry on the response of job creation and destruction to uncertainty. They conclude that of the types of frictions considered, only financial frictions are relevant as a channel through which uncertainty affects job flows.

Despite the consistency of my results with theirs in the overall directions of the effects of uncertainty on job creation and destruction, the results of Mecikovsky and Meier (2017) raise an important question for this paper. Their measure of industry-level vulnerability to financial frictions can be interpreted as dependence on external finance. One of the components they use in constructing their financial frictions measure is the share of employment at firms below 5 years of age in the industry, with the justification that young firms have larger borrowing costs. It is interesting, then, that I find a small and insignificant response of the detrended job creation rate of entrants to uncertainty. Also, the portion of the effect of financial uncertainty on the total job creation rate coming through the job creation rate of entrants, both detrended and non-detrended, is small compared to the portion of total jobs that are created by entrants. To further analyze this apparent contradiction in future research, I would attempt to directly measure the dependence on external finance of entering firms in a way that is as disaggregated as possible. A difference-in-difference exercise could potentially be conducted that compares entrant size across states or industries with chang-
ing financial regulations such as leverage requirements. This could help us find out to what extent the number of jobs created by entrants depends on the availability of external finance. On the exitor side, I have found that the rate of job destruction due to exiting establishments is not very important as a channel through which financial uncertainty affects the total job destruction rate. To understand this, it would be interesting to know what proportion of establishments (or firms) exit due to default. If financial constraints are important in exit decisions, it would make it all the more surprising that establishment exit contributes little to the effect of uncertainty on job destruction.

Financial uncertainty was found in this paper not to act on GDP growth through the job creation rate, even though a large portion of the variation in GDP growth is generated by financial uncertainty. This suggests that the effect of financial uncertainty on growth passes through other channels, as proposed by Gilchrist, Sim and Zakrajšek (2014).
Chapter 3

The Effects of Uncertainty Shocks in a Model with Firm Entry and Exit

3.1 Introduction

In the various studies of the impact of uncertainty on the economy, conflicting conclusions have been drawn as to the importance of the interaction between uncertainty and capital adjustment frictions in generating an economic downturn. Bloom et al. (2014) find that the real-options effect created by this interaction – where firms pause investment and disinvestment under high uncertainty because of the costliness of making an error – can generate a drop in GDP growth of 2.5% and conclude that uncertainty can be a major factor in driving the business cycle. On the other hand, Bachmann and Bayer (2013) argue, using a model calibrated to German business data, that firm-level uncertainty shocks do not cause business cycles of the magnitudes observed in the data. Mecikovsky and Meier (2017) question the presence of observable wait-and-see effects in the data, as they find that any significant effects of high uncertainty on variables such as firms’ investment and output act through financial constraints rather than through interaction with real frictions. Gilchrist, Sim and Zakrajšek (2014) find that financial distortions greatly amplify the response of investment
to uncertainty shocks as compared to a model with only capital adjustment constraints, in part by interacting with investment irreversibility. In an empirical analysis comparing the effects of uncertainty about financial variables to those of uncertainty about real activity variables, Ludvigson, Ma and Ng (2016) provide evidence that financial uncertainty has a causal effect on the economy, whereas real activity uncertainty does not. Basu and Bundick (2014) argue that the interaction of uncertainty with price stickiness generates the same comovement among consumption, hours, output and investment as observed in the data, which has been difficult to achieve using other types of frictions.

This paper studies another channel through which uncertainty could affect the economy: The life-cycle dynamics of firms. In chapter 2 of this dissertation I found, using vector autoregressions, that job creation by entering firms is not a very important channel for the influence of financial uncertainty on the overall job creation rate, and that job destruction by exiting firms is not very important for the influence of financial uncertainty on the overall job destruction rate. This chapter complements the previous one by studying the effects of uncertainty on a model economy with endogenous entry and exit of firms. Even though I found little importance of the effect of uncertainty on entry and exit on job creation and destruction rates, it could still be that the incorporation of endogenous entry and exit into a DSGE model with capital adjustment frictions causes the effects of uncertainty on aggregate values to change relative to a model in which entry and exit are exogenous. This would suggest that variation in the entry and exit rates of firms may be more important to growth than indicated by the empirical results of chapter 2.

In this paper I extend the Bachmann and Bayer (2013) and Bloom et al. (2014) models to include endogenous entry and exit of firms. My model includes non-convex capital adjustment costs and partially irreversible investment. The model is most similar to Bloom et al. (2014), however, unlike them, I do not include labor adjustment frictions. This is justified by the suggestion in Bloom (2009) that fixed costs of capital adjustment may be more necessary than labor frictions for replicating moments of the data. The first goal of my study is to find
the effects of uncertainty on the choices of entering and incumbent firms, such as entry decisions, capital accumulation and the timing of exit. The second is to study how the responses of aggregate variables and firm distributions to an uncertainty shock change when entry and exit are allowed to vary endogenously. In modeling entry and exit, I follow Clementi et al. (2015) and Clementi and Palazzo (2016). The presence of life-cycle dynamics in this model, as in Clementi et al. (2015), allows uncertainty to affect firms of different ages differently. Firms tend to start out smaller than average. Surviving firms tend to grow quickly until reaching a capital stock that is optimal in the long term, given the adjustment costs and irreversibility. At some point, a firm will get a sufficiently bad combination of idiosyncratic and aggregate productivity shocks and fixed continuation cost shocks such that it is optimal to exit. In this model, there can be no direct wait-and-see effect for potential entrants because they only get one chance to enter. But uncertainty shocks can still influence entry decisions through a potential entrant’s expectations. Clementi et al. (2015) discuss how the effects of a low aggregate TFP shock are amplified by endogenous entry and exit. In their model, such a shock heavily affects small firms and potential entrants, leading to a “missing generation effect”. A similar channel turns out to exist here with uncertainty shocks.

The assumptions of convex and non-convex adjustment costs and investment irreversibility are important to the results of this paper. There is a large literature on capital adjustment costs and their relationship with investment. Cooper and Haltiwanger (2006) argue that imposing both convex and non-convex adjustment costs improves the fit of a general equilibrium model of investment, compared to only one or the other type of costs. As they explain, the fixed adjustment costs can represent the disruption of production that can occur when firms expand their capacity, for instance by installing new machines which take time to install and to learn how to operate. The addition of partial investment irreversibility to the model has been justified in Cooper and Haltiwanger (2006) by the fact that investment is positive in approximately 80% of their observations, with only 10% of observations showing negative investment. The observed skewness in the investment distribution and lumpiness of
investment episodes, with relatively long periods of inaction followed by intense investment activity, has been taken as evidence of irreversibilities and non-convex adjustment costs in Caballero, Engel and Haltiwanger (1995) and Bachmann, Caballero and Engel (2013). Following the literature, this paper adopts both types of capital adjustment costs and partial irreversibility of investment. A fixed cost of continuation in the market is also imposed so that firms sometimes find it optimal to exit. There is a fixed and a convex cost of entry so that the measure and size of entering firms change over time.

3.2 Model

The model follows Khan and Thomas (2008, 2013), Clementi et al. (2015), Bloom et al. (2014) and Bachmann and Bayer (2013), with some important differences. The economy consists of a continuum of heterogeneous firms, a continuum of potential firms and a representative, infinitely-lived household. Time is discrete and agents discount future payoffs at the common rate $\beta$. The firms produce a homogeneous good in a competitive market according to a decreasing-returns production function $F$, using capital $k$ and labor $n$ as inputs. The good can be used as consumption or capital. Capital depreciates at the constant rate $\delta$ per period. Firms face both idiosyncratic and aggregate productivity shocks, denoted $\varepsilon$ and $Z$. The conditional standard deviation of the idiosyncratic productivity shocks $\sigma_\varepsilon$ is fixed, but the standard deviation of the aggregate productivity shocks $\sigma$ is time-varying. Continuing firms also face a fixed capital-adjustment cost, $\zeta_1 \sim_{i.i.d.} \phi_1$ with support $[0, \bar{\zeta}_1]$, which must be paid in order for next-period capital to differ from the depreciated value of this period’s capital. In addition, to adjust their capital from $k$ this period to $k'$ next period, they have to pay a convex cost $\xi(k,k')$. Unlike in Bloom et al. (2014), there are no labor adjustment costs. Capital purchases by the firm are partially irreversible; the resale price of capital is $\chi \in [0,1]$. To continue in the market this period, firms have to pay a random nonconvex continuation cost, $\zeta_0 \sim_{i.i.d.} \phi_0$, with support $[0, \bar{\zeta}_0]$. This makes it optimal for some firms to
exit. A firm that exits does not produce this period and cannot reenter later.

In each period, there is a measure one of potential firms which decide whether to enter the market. Clementi et al. (2015) also have endogenous entry and exit, but in their model the number of potential firms in each period varies so that the total measure of “blueprints” – that is, the total measure of existing firms plus the measure of potential entrants minus the measure of firms that have exited – remains constant. In their model, once a firm has exited, its blueprint can be reused by a new entrant. Here I choose to have a fixed measure of potential firms in each period so that the number of entrants is not constrained by the number of exitors and existing firms.

To enter with starting capital $\kappa$, a potential firm needs to pay a random fixed entry cost, $\zeta_e \sim_{i.i.d} \phi_e$ with support $[\zeta_e, \bar{\zeta}_e]$, and a convex cost $\xi_e(\kappa)$. Before making its entry choice, a potential firm receives a signal $\varepsilon$ about its next-period idiosyncratic productivity. If it decides to enter, it has to wait for one period to start producing. Thus a potential entrant could enter and exit in the next period without ever having produced.

The representative household is endowed with one unit of labor in each period and supplies labor to the firms at the competitively determined wage $w$. It also owns the firms, lends and borrows funds, and buys the good for consumption.

Firms’ investment, entry and exit decisions in each period generate a distribution $\mu$ over capital stocks $k$ and idiosyncratic productivities $\varepsilon$, where $\mu(k, \varepsilon)$ is the measure of firms with capital $k$ and idiosyncratic productivity $\varepsilon$. The state variables on which firms base their decisions consist of the idiosyncratic ones $(k, \varepsilon)$ and the aggregate ones $s = (Z, \sigma, \mu)$. In section 4, I will discuss how $\mu$ is proxied by aggregate capital according to the algorithm of Krusell and Smith (1998). The endogenous variables are all functions of the set of state variables. In the equations of the following sections, I omit the dependence on the state variables when it is clear and write, for example, $\zeta_0^*$ instead of $\zeta_0^*(k, \varepsilon; s)$. 
3.2.1 Incumbent firm’s problem

An incumbent firm (or incumbent) is defined as a firm that was in the market last period (either it produced last period or it was an entrant last period). An incumbent firm’s output is

\[ y = \varepsilon Z F(k, n), \quad (3.1) \]

where

\[ F(k, n) = k^\alpha n^\nu, \quad (3.2) \]

\[ \alpha + \nu < 1, \]

\[ \alpha, \nu > 0, \]

\( \varepsilon \) is the firm’s idiosyncratic productivity shock and \( Z \) is the aggregate productivity shock. The logs of the productivity shocks evolve as AR(1) processes:

\[ \ln(\varepsilon_t) = -\frac{\sigma_\varepsilon^2}{2(1 - \rho_\varepsilon^2)} + \rho_\varepsilon \ln(\varepsilon_{t-1}) + \tau_{\varepsilon,t} \quad (3.3) \]

with

\[ \tau_{\varepsilon,t} \sim \mathcal{N}(0, \sigma_\varepsilon^2), \]

and

\[ \ln(Z_t) = -\frac{\sigma_Z^2}{2(1 - \rho_Z^2)} + \rho_Z \ln(Z_{t-1}) + \tau_{Z,t} \quad (3.4) \]

with

\[ \tau_{Z,t} \sim \mathcal{N}(0, \sigma_Z^2). \]

The processes are defined in this way to facilitate experimenting with the variance, so that when \( \sigma_\varepsilon \) is changed, the unconditional mean of the process for \( \varepsilon \) stays the same. Similarly, we want the unconditional mean for \( Z \) to stay the same when \( \sigma_Z \) rises in the uncertainty shock experiments, so that responses to a rise in \( \sigma \) are not caused by an increase in the
unconditional mean of $Z$. $\tau_{\varepsilon,t}$ and $\tau_{Z,t}$ are independent across time and independent of each other and of the fixed adjustment costs. $\ln(\sigma_t)$ evolves as an AR(1) process with mixture of normals error.

The timing of incumbent firms’ decisions is as follows. In each period an incumbent firm first observes its idiosyncratic shock $\varepsilon$, the aggregate TFP shock $Z$ and the realization of its fixed continuation cost $\zeta_0$. Then it decides whether to continue or to exit. If it continues, it then observes the realization of the adjustment cost $\zeta_1$ and decides whether to adjust its capital to the optimal value or to let its capital depreciate. Given current capital stock $k$, a firm can let its capital depreciate to $(1 - \delta)k$ without paying any fixed adjustment cost. If a firm adjusts to capital stock $k'$, it pays the cost

$$
\xi(k, k') = \tau(k, k')\left(k' - (1 - \delta)k\right) + c_q\frac{(k' - (1 - \delta)k)^2}{k},
$$

where

$$
\tau(k, k') = 1\left\{k' > (1 - \delta)k\right\} + \chi 1\left\{k' < (1 - \delta)k\right\}
$$

and $\chi \in [0, 1]$ is the irreversibility parameter. The second term on the right-hand side of equation (3.5) is the quadratic adjustment cost; this allows firms with the same $\varepsilon$ but different $k$ to have different target capital levels. A firm starts the next period with the capital stock chosen in this period, i.e. there is a one-period time-to-build assumption.

The timing assumptions for incumbents are made to generate more heterogeneity in the firms’ actions and outcomes, as well as for simplicity of computation. By assuming that $\zeta_1$ is independent of $\zeta_0$ and not observed when the continuation decision is made, the exit decision can be characterized by the cutoff value $\zeta_0^*$. If firms were to observe their realizations of $\zeta_1$ at the same time as their realizations of all the other shocks, for each set of productivity shocks and capital, there would be a region in the space $S = [0, \bar{\zeta}_1] \times [0, \bar{\zeta}_0]$ in which all firms would both continue and adjust, another region in which all firms would continue but not adjust, and another in which all firms would exit. These regions might not be connected,
and would be more complicated to describe and work with than the simple cutoff rules when firms observe $\zeta_1$ after making their continuation decision. Furthermore, when firms observe $\zeta_1$ after the other shocks, they may make an initial choice to continue, based on the expected value over $\zeta_1$, that turns out to have been mistaken (they get a very high adjustment cost shock when they expected to invest a non-zero amount). The fact that such an outcome would be impossible in the case where firms observe all shocks at the same time implies that the latter case generates less heterogeneity in firms’ values.

Since the firm does not have labor adjustment costs, the labor choice solves a static problem. The firm’s labor demand is

$$n_d(k, \varepsilon; s) \equiv \arg\max_n \left\{ \varepsilon Z k^\alpha n^\nu - w(s)n \right\} = \left( \frac{\varepsilon Z k^\alpha}{w(s)} \right)^{1/(1-\nu)}$$

(3.6)

Define the firm’s flow profit as

$$\Pi(k, \varepsilon; s) \equiv \varepsilon Z F(k, n_d) - w(s)n_d = (1 - \nu) \left( \frac{\nu}{w(s)} \right)^{\frac{\nu}{1-\nu}} \left( \varepsilon Z \right)^{\frac{1}{1-\nu}} k^{\frac{\alpha}{1-\nu}}.$$  

(3.7)

The incumbent firm’s value function $V(k, \varepsilon; s)$ is defined in three steps. First consider the problem of a firm that has already decided to continue and has observed its realization of $\zeta_1$, and is deciding whether to adjust to the optimal next-period capital or not to adjust. If the firm chooses not to adjust, its capital will depreciate to

$$k^{na} \equiv (1 - \delta)k$$

by the next period. The optimal next period capital $k^a$ conditional on adjusting is defined by

$$k^a(k, \varepsilon; s) = \arg\max_{k'} \left\{ -\xi(k, k') + E \left[ m' V(k', \varepsilon'; s') \right] \right\},$$

(3.8)

where $m'$ is the stochastic discount factor to be defined below, and the expectation is taken
over the joint probability distributions of the state variables.

Let $V^a$ be the continuation value of a firm that has chosen to adjust to $k^a$ and $V^{na}$ the continuation value of a firm that has chosen no adjustment. Then

$$V^a(k, \varepsilon; s) = -\xi(k, k^a) + E\left[ m'V(k^a, \varepsilon'; s') \right]$$

(3.9)

and

$$V^{na}(k, \varepsilon; s) = E\left[ m'V(k^{na}, \varepsilon'; s') \right].$$

(3.10)

The value of adjusting is nonincreasing in the realization of $\zeta_1$. Therefore, given $(k, \varepsilon; s)$ there is a cutoff adjustment cost $\zeta_1^*$ such that a firm adjusts to $k^a$ if $\zeta_1 \leq \zeta_1^*$ and does not adjust otherwise. $\zeta_1^*$ is such that the firm is indifferent between choosing $k^a$ and choosing $k^{na}$, so

$$\zeta_1^*(k, \varepsilon; s) = \max \left\{ \min \left\{ \frac{V^a(k, \varepsilon; s) - V^{na}(k, \varepsilon; s)}{w}, \zeta_1 \right\}, 0 \right\}. \quad (3.11)$$

Now consider the firm’s choice whether to continue or exit, before $\zeta_1$ has been realized. The expected value of continuing, after paying the fixed continuation cost, is

$$V_1(k, \varepsilon; s) = \Pi(k, \varepsilon; s)+$$

$$\int_0^{\zeta_1^*} \left[ -w\zeta_1 + V^a(k, \varepsilon; s) \right] d\phi_1(\zeta_1) + \int_{\zeta_1^*}^{\bar{\zeta}_1} V^{na}(k, \varepsilon; s) d\phi_1(\zeta_1).$$

The value of exiting is just $\chi k$. So the firm is indifferent between exiting and continuing when

$$V_1(k, \varepsilon; s) - \zeta_0 = \chi k.$$ 

Therefore the cutoff value of $\zeta_0$ between exiting and continuing is

$$\zeta_0^* = \max \left\{ \min \left\{ V_1(k, \varepsilon; s) - \chi k, \bar{\zeta}_0 \right\}, 0 \right\}, \quad (3.12)$$
and the firm’s expected value before the realization of $\zeta_0$ is

$$V(k, \varepsilon; s) = \int_0^{\zeta_0} \left[ -\zeta_0 + V_1(k, \varepsilon; s) \right] d\phi_0(\zeta_0) + \int_{\zeta_0}^{\zeta^*} \chi k d\phi_0(\zeta_0). \quad (3.13)$$

### 3.2.2 Potential entrants’ problem

A potential entrant first observes its productivity signal $\varepsilon$ and its fixed entry cost $\zeta_e \sim \phi_e$, then decides whether to enter. If it does not enter, it cannot enter at a later date, and its reservation payoff is zero. If it enters with capital $\kappa$, it pays the fixed cost $\zeta_e$ and a convex cost,

$$\xi_e(\kappa) = \kappa + \frac{\gamma_1}{2} \kappa^2. \quad (3.14)$$

It begins producing the following period, and from that point its problem becomes that of an incumbent firm. Thus the potential entrant’s problem is summarized by the equations

$$\kappa^*(\varepsilon; s) \equiv \text{argmax} \left\{ -\xi_e(\kappa) + E \left[ m'V(\kappa, \varepsilon'; s') \right] \right\}, \quad (3.15)$$

determining its optimal entering capital stock should it decide to enter,

$$V_e(\varepsilon; s) \equiv -\xi_e(\kappa^*(\varepsilon; s)) + E \left[ m'V(\kappa^*(\varepsilon; s), \varepsilon'; s') \right], \quad (3.16)$$

determining the firm’s value if it does enter with the optimal capital stock, and

$$\zeta_e^*(\varepsilon, s) = \max \left\{ \min \left\{ V_e(\varepsilon; s), \zeta_e \right\}, \zeta_e \right\}, \quad (3.17)$$

such that a potential entrant with state variables $(\varepsilon; s)$ enters, with initial capital $\kappa^*(\varepsilon; s)$, if and only if $\zeta_e < \zeta_e^*(\varepsilon; s)$. 

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3.2.3 Household’s problem

The household chooses sequences \( \{C, N, a'\} \) of consumption, labor and assets to maximize its value function

\[
W(C, N) = U(C, N) + \beta E[W(C', N')]
\]  

(3.18)

subject to

\[
C + a' \leq wN + (1 + r)a,
\]

where the wage \( w \) and interest rate \( r \) are taken as given by the household, and \( U(C, N) \) is the flow utility function. The first-order conditions of this problem lead to the following equalities, assuming interior solutions:

\[
w = -\frac{U_2(C, N)}{U_1(C, N)},
\]  

(3.19)

\[
\frac{1}{1 + r} = \beta \frac{U_1(C', N')}{U_1(C, N)},
\]  

(3.20)

where \( U_j \) refers to the partial derivative of the function \( U \) with respect to its \( j \)th argument and primes refer to next-period values of variables. The term on the right-hand side of equation (3.20) is defined as the stochastic discount factor,

\[
m' = \beta \frac{U_1(C', N')}{U_1(C, N)}.
\]  

(3.21)

By giving firms the same stochastic discount factor as households, I incorporate the household’s problem into the firm’s problem, as noted by Khan and Thomas (2008, 2013). Define

\[p \equiv U_1(C, N).\]
As in Khan and Thomas (2008, 2013) and Bloom et al. (2014), I use the utility function

\[ U(C, N) = \ln(C) - \theta N. \]  \hspace{1cm} (3.22)

This specification is chosen for simplicity, as it makes it unnecessary to forecast both the wage and the marginal utility of consumption. Combining the household’s first-order conditions with equation (3.22) leads to the expression for wage,

\[ w = -\frac{U_2(C, N)}{U_1(C, N)} = \theta C. \]  \hspace{1cm} (3.23)

Thus, the labor supply is infinitely elastic.

### 3.3 Stationary equilibrium

#### 3.3.1 Definition

The stationary equilibrium of this economy is defined by the equations in this section. These are similar to the equations determining the solutions to the agents’ problems above, except that here the aggregate state variables do not vary. First, the aggregate TFP is fixed at its unconditional mean.

\[ Z_t \equiv Z = 1. \]

Assume that the distributions \( \phi_0 \) and \( \phi_1 \) of a firm’s continuation costs \( \zeta_0 \) and adjustment costs \( \zeta_1 \), respectively, are both uniform on their supports.

The optimal choice of next-period capital conditional on adjustment and continuation is made as above.

\[ k^a(k, \varepsilon) = \arg\max_{k'} \left\{ -\xi(k, k') + \beta E \left[ V^{ss}(k', \varepsilon')|\varepsilon \right] \right\}, \]  \hspace{1cm} (3.24)
where $V^{ss}$ is the steady-state value function of the firm. If a firm chooses not to adjust, it starts next period with the depreciated capital stock,

$$k^{na}(k, \varepsilon) = (1 - \delta)k.$$

The value functions of the firm conditional on adjustment and no adjustment, respectively, are defined as

$$V^a_1(k, \varepsilon) = -\xi(k, k^a) + \beta E[V^{ss}(k^a, \varepsilon')|\varepsilon],$$

$$V^{na}_1(k, \varepsilon) = \beta E[V^{ss}(k^{na}, \varepsilon')|\varepsilon].$$

The cutoff fixed cost for adjustment is defined as

$$\zeta^*_1(k, \varepsilon) = \max \left\{ \min \left\{ \frac{V^a_1(k, \varepsilon) - V^{na}_1(k, \varepsilon)}{w^{ss}}, \bar{\zeta}_1 \right\}, 0 \right\},$$

and the value function of the firm conditional on continuation is

$$V^{ss}_0(k, \varepsilon) = \Pi(k, \varepsilon; w) + \left(1 - \frac{\zeta^*_1}{\zeta_1} \right) V^{na}_1(k, \varepsilon) - w \frac{(\zeta^*_1)^2}{2\zeta_1} + \frac{\zeta^*_1}{\zeta_1} V^a_1(k, \varepsilon).$$

Equation (3.28) defines the value of continuing as profits plus the expected value over $\zeta_1$ of the firm, given that it chooses the optimal capital level for next period. The cutoff value of $\zeta_0$, determining whether a firm continues or exits, is defined as

$$\zeta^*_0(k, \varepsilon) = \max \left\{ \min \left\{ V^{ss}_0(k, \varepsilon) - \chi k, \bar{\zeta}_0 \right\}, 0 \right\},$$

and the steady-state value of the firm before its fixed costs have been realized is

$$V^{ss}(k, \varepsilon) = \left(1 - \frac{\zeta^*_0}{\zeta_0} \right) \chi k - \frac{(\zeta^*_0)^2}{2\zeta_0} + \frac{\zeta^*_0}{\zeta_0} V^{ss}_0(k, \varepsilon).$$

Since there is a continuum of firms subject to the same laws of motion for productivity and
adjustment costs, the law of large numbers implies that the proportion of firms taking any possible action (continuation or exit, adjustment or no adjustment) is equal to the probability of a given firm taking that action. Therefore the total adjustment cost paid by firms at state \((k, \varepsilon)\), denoted \(AC(k, \varepsilon)\), is determined as the weighted sum of the costs paid when taking either type of action.

\[
AC(k, \varepsilon) = \left(1 - \frac{\zeta^*_0}{\zeta_0}\right)\chi k + \frac{(\zeta^*_0)^2}{2\zeta_0} + \frac{\zeta^*_0}{\zeta_0} \left[\left(1 - \frac{\zeta^*_1}{\zeta_1}\right)\xi(k, k^n) + \frac{w(\zeta^*_1)^2}{2\zeta_1} + \frac{\zeta^*_1}{\zeta_1} \xi(k, k^a)\right].
\] (3.31)

In the two next equations \(\kappa^*\), a potential firm’s initial capital choice conditional on entering, and the fixed entry cost cutoff \(\zeta^*_e\) are defined as functions of the idiosyncratic productivity signal \(\varepsilon\).

\[
\kappa^*(\varepsilon) = \arg\max_{\kappa > 0} \left\{ -\kappa - \gamma_1 \kappa^2 + \beta E\left[V(\kappa, \varepsilon')|\varepsilon\right] \right\},
\] (3.32)

\[
\zeta^*_e(\varepsilon) = \max \left\{ \min \left\{ -\kappa^* - \gamma_1 (\kappa^*_e)^2 + \beta E\left[V(\kappa^*, \varepsilon')|\varepsilon\right], \zeta^*_e, \zeta_e \right\} \right\}.
\] (3.33)

The distribution of entering firms is then given by

\[
EM(k, \varepsilon) = \begin{cases} 
\left(\frac{\zeta^*_e(\varepsilon) - \zeta_e}{\zeta^*_e - \zeta_e}\right) \bar{\mu}(\varepsilon) & \text{if } k = \kappa^*(\varepsilon), \\
0, & \text{otherwise}
\end{cases}
\] (3.34)

where \(\bar{\mu}\) is the ergodic density of the process for \(\varepsilon\). Individual and aggregate entry costs are given by

\[
EC_0(\varepsilon) = \frac{(\zeta^*_e)^2 - \zeta_e}{2(\zeta^*_e - \zeta_e)} + \left(\frac{\zeta^*_e - \zeta_e}{\zeta^*_e - \zeta_e}\right) \xi^*(\varepsilon) + \frac{\gamma_1 (\kappa^*(\varepsilon))^2}{2},
\] (3.35)

\[
EC = \int EC_0(\varepsilon) \bar{\mu}(\varepsilon).
\] (3.36)

Finally, the aggregate equilibrium conditions are

\[
Y = \left(\frac{\nu}{w}\right)^\frac{\nu}{1-\nu} \int_k \int_{\varepsilon} \frac{\zeta^*_0(k, \varepsilon)}{\xi_0} \varepsilon^{\frac{1}{1-\nu}} k^{\frac{\alpha}{1-\nu}} d\mu(k, \varepsilon),
\] (3.37)
\[ C = Y - AC - EC, \quad (3.38) \]

\[ w = \theta C, \quad (3.39) \]

\[ N = \left( \frac{\nu}{w} \right)\frac{1}{1-\nu} \int \int \left( \frac{\zeta_\theta(\nu, \varepsilon)}{\zeta_0} \right) \varepsilon^{1-\nu} k^{\alpha-\nu} d\mu(k, \varepsilon). \quad (3.40) \]

The ergodic distribution of individual states \( k \) and \( \varepsilon \) obeys

\[ \mu(k, \varepsilon) = (\Gamma \mu)(k, \varepsilon) + EM(k, \varepsilon), \quad (3.41) \]

where \( \Gamma \) is the transition function over \( \mu \) given by

\[
\Gamma \mu(k', \varepsilon'; s) = \int \int \frac{\zeta_\varepsilon}{\zeta_0} \Pr(\varepsilon'|\varepsilon) \times \left[ \left( 1 - \frac{\zeta_1}{\zeta_\varepsilon} \right) \mathbf{1}\{k'^{\alpha}(k, \varepsilon) = k'\} + \frac{\zeta_1}{\zeta_\varepsilon} \mathbf{1}\{k^{\alpha}(k_i, \varepsilon_j) = k'\} \right] d\mu(k, \varepsilon). \quad (3.42) \]

### 3.3.2 Numerical approximations

Since capital is a state variable, it is simpler to calculate the value and decision functions using a grid for capital. I use a grid that is closed under depreciation (the ratio of the \( j \)-th to the \((j-1)\)-th element of the grid is \( \frac{1}{1-\delta} \), where \( \delta \) is the capital depreciation rate) with minimum value approximately 0.01 and maximum value approximately 6.5. The grid \( \Xi \) and transition matrix \( P_\varepsilon \) for \( \varepsilon \) are constructed using Tauchen’s (1986) approximation with parameters \( \rho_\varepsilon \) and \( \sigma_\varepsilon \) determined from the calibration. The two grids for \( Z \) and its transition matrices are constructed using an extension of Tauchen’s method to a variable with two possible standard deviation values. Denote the grid for \( k \) by \( \Lambda = \{k_1, ..., k_{n_k}\} \), the grid for \( \varepsilon \) by \( \Xi = \{\varepsilon_1, ..., \varepsilon_{n_\varepsilon}\} \) and the grids for \( Z \) by \( \Upsilon_L = \{Z_{1,L}, ..., Z_{n_z,L}\} \) and \( \Upsilon_H = \{Z_{1,H}, ..., Z_{n_z,H}\} \), respectively. Then all the equations above have approximate counterparts with discrete state
variables. For instance, equation (3.42) is approximated by

\[
\Gamma \mu(k_{i''}, \varepsilon_{j'}) = \sum_{i=1}^{n_k} \sum_{j=1}^{n_\varepsilon} \frac{\zeta_0^*(k_i, \varepsilon_j)}{\zeta_0} P_{\varepsilon}(\varepsilon_j, \varepsilon_{j'}) \\
\times \left( \frac{\zeta_1^*(k_i, \varepsilon_j)}{\zeta_1} \mathbb{1}\{k^a(k_i, \varepsilon_j) = k_{i''}\} + \left(1 - \frac{\zeta_1^*}{\zeta_1}\right) \mathbb{1}\{k^{na}(k_i, \varepsilon_j) = k_{i''}\}\right) \mu(k_i, \varepsilon_j).
\]

(3.43)

### 3.3.3 Calibration

I calibrate the model in stationary equilibrium to match certain moments of the data. A period equals one year. Table 1 shows the calibration targets and model values, and Table 2 shows the corresponding parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Target</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital-output ratio</td>
<td>2.1</td>
<td>2-3</td>
<td>standard</td>
</tr>
<tr>
<td>Hours</td>
<td>0.35</td>
<td>0.25-0.33</td>
<td>standard</td>
</tr>
<tr>
<td>Entry/exit rate</td>
<td>7.2%</td>
<td>8.7%</td>
<td>Clementi et al. 2015</td>
</tr>
<tr>
<td>Exit rate age 1</td>
<td>17%</td>
<td>17%</td>
<td>Clementi et al. 2015</td>
</tr>
<tr>
<td>Exit rate age 2</td>
<td>11%</td>
<td>11%</td>
<td>Clementi et al. 2015</td>
</tr>
<tr>
<td>Relative entry size</td>
<td>0.59</td>
<td>0.55</td>
<td>Lee and Mukoyama 2015</td>
</tr>
<tr>
<td>Average investment rate</td>
<td>10.1%</td>
<td>12.2%</td>
<td>Cooper and Haltiwanger 2006, LRD</td>
</tr>
<tr>
<td>Prop. investment spikes</td>
<td>18.9%</td>
<td>18.6%</td>
<td>Cooper and Haltiwanger 2006, LRD</td>
</tr>
<tr>
<td>Survival rate after 5 yrs</td>
<td>50%</td>
<td>45%</td>
<td>Clementi et al. 2015</td>
</tr>
</tbody>
</table>

**Note:** LRD is the Longitudinal Research Database, using large manufacturing firms from 1972 to 1988. Investment spikes are defined as instances where a firm’s investment is more than 20% of its existing capital.
<table>
<thead>
<tr>
<th>δ</th>
<th>β</th>
<th>α</th>
<th>ν</th>
<th>c_q</th>
<th>ζ₀</th>
<th>ζ₁</th>
<th>ζₑ</th>
<th>ζₑ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.91</td>
<td>0.98</td>
<td>0.285</td>
<td>0.46</td>
<td>0.08</td>
<td>0.26</td>
<td>0.007</td>
<td>0.01</td>
<td>0.06</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>γ₁</th>
<th>θ</th>
<th>ρₑ</th>
<th>σₑ</th>
<th>χ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>2.8</td>
<td>0.91</td>
<td>0.075</td>
<td>0.7</td>
</tr>
</tbody>
</table>

Note: δ is the capital depreciation rate, β the discount factor, α capital output elasticity, ν labor output elasticity, c_q quadratic cost factor, ζ₀ the upper bound for fixed continuation cost, ζ₁ the upper bound for fixed adjustment cost, ζₑ and ζₑ the bounds for fixed entry cost, γ₁ the quadratic entry cost factor, θ the disutility of labor, and ρₑ and σₑ the persistence and standard deviation of ln(ε).

### 3.3.4 Steady state experiments

I run three experiments on the steady state economy. In the first, I start with the parameters at the calibrated values and gradually increase σₑ, the variance of the process for idiosyncratic productivity, common to all firms. Since the process for ε is

\[ \ln(ε') = ρₑ \ln(ε) - \frac{σₑ^2}{2(1 - ρₑ^2)} + σₑω, \]

with \( ω \sim \mathcal{N}(0, 1) \), an increase in σₑ preserves the unconditional mean of ε'.

In the second experiment, I start with the calibrated parameter values and gradually increase the perceived uncertainty ˆσₑ from its initial value, but not the actual uncertainty σₑ. That is, agents choose their decision rules taking ˆσₑ as the conditional standard deviation of ε, but the actual process followed by ε has standard deviation σₑ. This experiment is meant to isolate the effects of agents’ perception of uncertainty from the effects of the actual variance of the productivity shocks. As can be seen from the measurements of professional forecasters probability scores in chapter 1 of this thesis, forecasters’ perceived uncertainty about a variable is sometimes very different from an ex-post estimate of the variance of
that variable. It is useful to know how this difference affects agents’ actions, because this could tell us whether it would be worth making an effort to find more “precise” measures of uncertainty.

The first two experiments involve general equilibrium. In the third experiment I find the stationary partial equilibrium with the wage fixed as $\sigma_\varepsilon$ increases. The purpose is to isolate the impact the consumer side of the market has on changes in steady-state values as the variance of the productivity shock increases (the difference between the general equilibrium values and the partial equilibrium values gives the effect of general equilibrium). This can help to understand the role of the household’s preferences and choices in recursive general equilibrium.

Each of the graphs in Figures 3.1-3.4 shows the results from all three experiments for a single variable. For instance, the left hand side of Figure 3.1 plots the changes in the aggregate steady-state capital stock as $\sigma_\varepsilon$ increases (solid line), as the perceived standard deviation $\hat{\sigma}_\varepsilon$ increases (line with circles), and as $\sigma_\varepsilon$ increases with wage fixed (dashed line).
Figure 3.1: Aggregate capital (top) and aggregate output (bottom)
Figure 3.2: aggregate employment and consumption
Figure 3.3: Aggregate investment and wage
In the stationary equilibrium experiments there is no wait-and-see effect because the change in the productivity variance is recognized to be permanent. The effect of an increase in uncertainty here is to increase activity: Capital, output, employment, consumption and wage all rise. This operates through the convexity of profits in productivity, which causes firms’ value functions to increase at a higher rate in capital (Oi 1961). Firms produce more now and invest more to be able to produce more in the future. Consumption increases because output increases at a higher rate than the total capital adjustment costs that must be paid, and because the demand for labor (and labor income) increases. The only variable in the graphs that decreases is the rate of entry and exit. This can be explained by the following argument: As the variance of the idiosyncratic productivity shock increases, the proportion of firms facing very high and very low productivity shocks increases. The expected return to staying in business rises, especially for larger firms. This effect dominates the effect of the very low shocks.

The partial equilibrium responses to an increase in uncertainty are much stronger than those in general equilibrium. For instance, an actual increase in the standard deviation of
productivity from 0.075 to 0.085 causes a more than 100% increase in output in partial equilibrium, whereas in general equilibrium the increase is only about 12%. Capital and employment both increase by about 250% in partial equilibrium, compared to only about 5% in general equilibrium. General equilibrium effects mitigate the expansionary effect of an increase in uncertainty through the rise in wage. When uncertainty rises with the wage fixed, firms earn more profits by producing more and investing more, without having to pay more to their factors of production (because the marginal utility of consumption is constant in steady state, the interest rate, defined by \( \frac{1}{1+r} = \beta \), is automatically fixed here). This leads to a large increase in output, which allows the household increase consumption by about 225%. However, consumption increases at a lower rate than output because the return to savings is higher, so that investment increases at a higher rate than consumption. In addition, the capital adjustment costs that must be paid are greater with larger variance of the idiosyncratic shock, since the actual adjustment that takes place is more. This further mitigates the increase in consumption.

In Figures 3.1-3.4, the effects of a change in only perceived uncertainty are close to those when both perceived and actual uncertainty change, at least compared to the changes in partial equilibrium. This suggests that it is mainly the perception of a larger spread in productivity, rather than an actual increased spread in productivity, that causes the variables’ responses. The main difference between the perceived uncertainty and true uncertainty experiment outcomes is the proportion of firms with very high or very low idiosyncratic productivity shocks. When firms get very low productivity shocks they are likely to exit (recall that firms observe their actual productivity before choosing this period’s actions); when they get very high productivity shocks they are likely to make a large positive investment, in accordance with the lumpy investment idea. Therefore the exit rate is higher for the true uncertainty experiment than for the perceived uncertainty experiment, at any value of \( \sigma_\varepsilon \) or \( \hat{\sigma}_\varepsilon \).

Capital and output increase at a higher rate in the perceived-uncertainty experiment than in the true-uncertainty experiment. This comes from the fact that a smaller proportion
of firms is exiting in the perceived uncertainty experiment. Consumption increases by less in the perceived uncertainty experiment because more resources are being used for capital adjustment.

3.4 Recursive general equilibrium

Given the functional forms of the firms’ production function and household’s utility function, and given the random processes for the idiosyncratic productivity shocks, aggregate productivity shock and standard deviation of the aggregate productivity shock, a recursive general equilibrium in this model is defined by the following conditions.

1. Incumbent firms choose policy functions \((k^a, k^{na}, \zeta_0^*, \zeta_1^*)\) to maximize their value function \(V\) at every value of the state variables \((k, \varepsilon; s)\), according to equations (3.9) to (3.13).

2. Potential entrants choose entering capital \(\kappa^*\) and the fixed-cost entry cutoff \(\zeta_e^*\) to maximize their value function, given the expected value function for incumbents, according to equations (3.15) to (3.17).

3. The representative household chooses sequences \(\{C, N, a'\}\) of consumption, labor supply and asset holdings to maximize its value function \(W\) in equation (3.18).

4. Markets clear in each period: The wage \(w\) is such that aggregate labor demand equals labor supply, and the resource constraint

\[ Y - AC - EC - C = 0 \]

holds, where \(Y\) is aggregate output defined in equation (3.37) (where the variables here are functions of \((k, \varepsilon; s)\)), \(AC\) equals the aggregate adjustment costs of incumbents defined in equation (3.31), \(EC\) equals the aggregate entry costs defined in equation (3.36), and \(C\) is
the household’s consumption. Imposing the stochastic discount factor

\[ m' = \beta \frac{U_1(C', N')}{U_1(C, N)} \]

on firms’ decisions ensures that the loans market clears.

5. The transition over \( \mu \) is given by

\[ \mu' = \Gamma(\mu) + EM \] (3.44)

given \( s = (Z, \sigma, \mu) \), where

\[
\Gamma(\mu)(k', \varepsilon') = \int \int \left( \frac{\zeta_0(k', \varepsilon; s)}{\zeta_0} \right) \left[ \left( \frac{\zeta_1(k', \varepsilon; s)}{\zeta_1} \right) \mathbf{1}\{k' = k^a(k, \varepsilon; s)\} + \left(1 - \frac{\zeta_1(k', \varepsilon; s)}{\zeta_1}\right) \mathbf{1}\{k' = k^{na}(k, \varepsilon; s)\} \right] P_\varepsilon(\varepsilon' | \varepsilon)d\mu(k, \varepsilon)
\]

where

\[
EM(k', \varepsilon'; s) = \int \mathbf{1}\{k' = \kappa^*(\varepsilon; s)\} P_\varepsilon(\varepsilon' | \varepsilon)d\bar{\mu}(\varepsilon)
\] (3.45)

is the distribution of entrants over capital and idiosyncratic productivity. \( \mu(k, \varepsilon) \) is the measure of firms with capital \( k \) and idiosyncratic productivity \( \varepsilon \) that have entered last period or previously and that do not exit this period - that is, those firms that produce this period.

6. Rational expectations hold: The agents know the transition function for \( \mu \) and incorporate this expectation of next-period’s \( \mu \) into their decision rules.

To be able to solve the model, some approximations need to be made. I discretize the state variables \( k, \varepsilon, Z, \sigma \), so that the value and policy functions become arrays. \( \sigma \) can assume just
two values, \( \sigma_L \) and \( \sigma_H \), and follows a Markov chain with transition matrix \( P_\sigma \), defined by

\[
\Pr[\sigma' = \sigma_L|\sigma = \sigma_L] = 0.95,
\]

\[
\Pr[\sigma' = \sigma_L|\sigma = \sigma_H] = 0.3.
\] (3.46)

The productivity shocks \( \varepsilon \) and \( Z \) are discretized according to Tauchen (1986). There are two grids, \( Z_L \) and \( Z_H \), for \( Z \), one corresponding to \( \sigma_L \) and one to \( \sigma_H \). The transition matrix from values of \( Z \) on \( Z_L \) to \( Z_H \) approximates the probabilities of moving from each point on the \( Z_L \) grid to each point on the \( Z_H \) grid in a way consistent with the Tauchen (1986) method.

In a full rational expectations equilibrium, agents can predict future prices conditional on the realizations of the shocks. In this model, since prices depend on the whole distribution \( \mu \) of firms over \((k, \varepsilon)\), it is infeasible for agents to predict prices this way, as they would be integrating over an infinite-dimensional space to find expected values. Therefore, as in Thomas (2003), Khan and Thomas (2008, 2013), Bachmann, Caballero and Engel (2013), and Bloom et al. (2014), I proxy the argument \( \mu \) in the equilibrium value, expected value and policy functions by the aggregate capital stock \( K = \int_k \int_\varepsilon kd\mu(k, \varepsilon) \), then check whether forecasts based on this proxy generate sufficiently small forecast errors. Young (2007a) demonstrates that in a similar model, the additional knowledge contained in higher moments of the firm distribution would not help agents make significantly better forecasts. It is not certain that this holds for the model in this paper, but the forecast rules generate 100-period ahead forecasts for \( K \) that are within 15% of the true values, and for \( p = MU_C \) that are within 5%. Log-linear forecasting rules are assumed for both \( K \) and \( p \), the marginal utility of consumption, i.e. I assume that agents predict using

\[
\ln(p) = \alpha_p(Z, \sigma, \sigma_{-1}) + \beta_p(Z, \sigma, \sigma_{-1}) \ln(K),
\] (3.47)

\[
\ln(K') = \alpha_K(Z, \sigma, \sigma_{-1}) + \beta_K(Z, \sigma, \sigma_{-1}) \ln(K).
\] (3.48)
The linear forecast coefficients \((\alpha_p, \beta_p)\) for \(\ln(p)\) and \((\alpha_K, \beta_K)\) for \(\ln(K)\) are allowed to depend on \((Z, \sigma, \sigma_{-1})\) as in Bloom et al. (2014), who argue that inclusion of the lagged aggregate productivity variance in the forecasting rule improves the forecast.

As in Khan and Thomas (2008, 2013), the solution method alternates between an inner and an outer loop. In the inner loop, the model is simulated for \(T = 4000\) periods, and the OLS coefficients on \(\ln(K)\) and \(\ln(p)\) in the forecasting rule are estimated. In the simulation of the model neither \(p\) nor \(K\) are restricted to follow the forecasting rules. \(p\) is calculated in each period from the aggregate resource constraint, and \(K\) is computed from firms’ previous-period decision rules, which determine the distribution \(\mu\). In the outer loop the firms’ value and policy functions are calculated using the latest \((\alpha_p, \beta_p)\) and \((\alpha_K, \beta_K)\) in the firms’ forecasts (dampening is used as I found this produces faster convergence). The iteration is continued until the 10-year-ahead forecasts for \(p\) and \(K\) lie within 5% of the actual values found in the simulation. The \(R\)-squared statistics for the OLS regressions for equations (3.47) and (3.48) are all above 0.99.

### 3.4.1 Background results

The correlation coefficient between consumption and output in the converged model is 0.80, and between output and lagged consumption is 0.89. The correlation between entry and output is 0.37 (compared to 0.40 in Campbell 1998), the correlation between output and lagged entry is 0.24, and between output and lead entry is 0.29. The correlation between output and the exit rate is -0.63 (compared to -0.78 in Campbell 1998), between output and lagged exit it is -0.16 and between output and lead exit it is -0.51.

Figures 5-7 are shown to help us understand the variables’ dynamics as they appear in the impulse response graphs. Figure 5 shows the probabilities of continuation by incumbent firms as a function of their capital stock \(k\) when \((\varepsilon; Z, K)\) is set to \(\varepsilon = 1\), \(Z = 1\), and \(K = 4\), for all four possible configurations of the current and lagged standard deviation of aggregate
productivity \((\sigma, \sigma_{-1})\).

For these values of the state variables \((\varepsilon; Z, K)\), the probability of continuation increases until capital is around 2, then decreases for larger capital. The continuation probability decreases for very large firms because the optimal capital stock at these values of the state variables is lower than 2. Shedding excess capital becomes more and more expensive as a firm gets larger because of the convex adjustment costs. This makes it optimal for very large firms to exit rather than paying these costs if they get a large draw of the fixed continuation cost.

For other values of the state variables, with low to medium idiosyncratic and aggregate productivity, the shape of the graph is similar, but shifted out for higher values of idiosyncratic and aggregate productivity and lower values of aggregate capital. If idiosyncratic and aggregate productivity are high enough, there is no decreasing part of the graph over the entire range of capital, as in Figure 3.4.1 below. The change in the shape of the graph for different values of the current and lagged standard deviation of productivity is more complicated:
For low levels of aggregate capital, the decreasing part of the graph is shifted inwards for higher $\sigma$, whereas for high levels of aggregate capital it is shifted out when $\sigma$ is higher. Since most firms have less than 2 units of capital in steady state (see Figure 3.6 below, which plots the steady-state measure of firms at each possible value of capital and idiosyncratic productivity), the more relevant range of capital values is the one over which the continuation probability is increasing. This observation is important in interpreting the reactions of potential entrants to an uncertainty shock.

Figure 3.6: Stationary measure of firms

Figure 3.4.1 shows the continuation probability over values of capital for $\varepsilon = 1.15$, $Z = 1.02$ if $\sigma$ is low or $Z = 1.03$ if $\sigma$ is high, $K = 5.4$, and all four possible configurations of the current and lagged standard deviations $(\sigma, \sigma_{-1})$. 
3.4.2 Impulse responses

Each of Figures 3.8 to 3.19 below plots the impulse response function of a variable to an uncertainty shock. An uncertainty shock is defined as a period of imposed high variance of the aggregate productivity shock. I consider shocks lasting 1 period, 2 periods and 5 periods. I simulate 100,000 economies, each with 95 periods, and impose high variance $\sigma$ from period 70 to period $70 + t_0$, where $t_0$ takes the values 0, 1, and 4. From period $70 + t_0 + 1$ on, the economy is allowed to evolve normally again (that is, the process for the variance of the productivity shock follows its Markov chain as in equation (3.46)). The value of the variable of interest is averaged across economies. The impulse response at period $t \geq 70$ is measured as the percentage difference between the average value of the variable at period $t$ and its
average value at period 69, as in Bloom et al. (2014). Figures 3.8-3.15 show the impulse responses of the total measure of firms, the measure of entrants and of exitors, the average capital of exitors, of entrants and of incumbents, the output of entrants and of incumbents, and the employment of entrants and of incumbents, for uncertainty shocks lasting one period, 2 periods and 5 periods.

Figure 3.8 shows that an uncertainty shock leads to an immediate and sustained decrease in the measure of firms. Figure 3.9 below explains this as being mainly caused by a decreased number of entrants.
The top graph in Figure 3.9 shows that immediately after the shock there is a very large drop of about 5.5% in the measure of entrants. Since in normal times entrants make up around 7 to 9 percent of all firms by measure, this drop leads to a simultaneous drop by
over 0.4% in the total measure of firms. The decrease in entrants is compounded by a small initial increase in exitor measure of around 0.7%. This increase comes from the increased spread in the aggregate productivity shock (recall that these graphs are based on the average of many economies with different paths of aggregate productivity), so that on average more firms lie in the exit region. After the initial onset of the shock, firms adjust to expecting further high uncertainty for a while, as the probability of high uncertainty next period is 0.7 when uncertainty this period is high. Fewer firms now exit because surviving larger firms have responded to the high uncertainty by investing less (see Figure 3.19 below) and because the total measure of firms is less; the average size of exitors slightly falls because of this adaptation by firms, and because the overall average capital stock of firms is smaller.

By the next period after the initial shock (period 2 in the graph), the measure of entrants has risen back to only 2 percent less than its pre-shock value in Figure 3.9. This is the same for the 1-period, 2-period and 5-period shock experiments. This bounce back in entrant measure is most likely caused by the decreased interest rate, which comes from overall decreased demand for investment by incumbent firms. It can also be interpreted in terms of consumers’ actions: The household correctly expects output and consumption to decrease over the period from time 1 to time 5. Therefore the time-\((t+1)\) marginal utility of consumption is higher than its value at time \(t\) for a few periods, making the expected interest rate lower than usual. This makes it more worthwhile for potential firms to enter in period 2 compared to period 1, and the measure of entrants rises. The measure of entrants returns to the pre-shock level after around 7 periods and stays there for the rest of the sample period. Mechanically, the measure of entrants falls for a only short time because aggregate capital also falls, which in turn makes entry more profitable (aggregate capital, as a state variable in the computation of firms’ value functions, is inversely related to value at each idiosyncratic capital and productivity level). Intuitively, this corresponds to business conditions becoming better because there are fewer firms in the market, opening up possibilities for new entrants.

The temporary drop in entrants and increase in exitors generate a much longer-term dip in
the total measure of firms, as seen in Figure 3.8. The measure of firms starts to rise after 5 periods, but it does not return to its initial level until around period 20. This corresponds to the “missing generation effect” discussed by Clementi et al. (2015) and Siemer (2014), where the effects of a negative first-moment aggregate TFP shock are amplified and prolonged by a lack of new entrants to replace increasing numbers of exiting firms. Here the missing generation effect is caused by the disproportionate negative impact of high uncertainty on small firms, which tend to be younger. Precisely because firms start out small and small firms need a higher idiosyncratic productivity in order to continue, young firms that have survived after a few years tend to have higher than average productivity. Once a firm has grown to a certain size, it is less likely to exit with a bad productivity shock unless it is at the very high end of the capital range. Thus, older firms (which tend to be larger, as negative investment is rarely undertaken because of the partial irreversibility of investment) are less productive on average than younger ones.

Figure 3.10 below shows that the average capital stock of entrants, defined as the total capital of entrants divided by the total measure of entrants, rises by 0.6% just after the shock, then declines quickly. Seeing the higher level of uncertainty, potential entrants with low idiosyncratic productivity signals predict that the likelihood of having to exit in the next period or soon after is greater than in normal times. Such an outcome would lead to a negative lifetime value, worse than the zero reservation value of staying out. The productivity signal of a potential firm now has to be quite high, or the fixed random entry cost low, for it to be worth entering, and with higher signal, a higher initial capital stock is optimal. Lee and Mukoyama (2015) note that in the Annual Survey of Manufactures (ASM) data the average size of entering plants in terms of labor, relative to incumbents, is about 25% smaller in booms than in recessions.

It may also be that potential firms with a given idiosyncratic productivity signal enter with higher capital than in normal times. In a sense, capital is more valuable under high uncertainty due to the higher probabilities of extreme aggregate productivity shocks — if a
very low shock hits that leads to exit, a higher exit value is obtained with more capital (since it can be resold at a fraction of its value without paying any adjustment costs), and if a very high shock hits, more profits can be obtained immediately without paying adjustment costs to grow.

Figure 3.10: Average capital of entrants (top) and of incumbents (bottom)
The graph of entrants’ average capital in Figure 3.10 helps to explain the post-shock behavior of entrants’ total capital, shown in Figure 3.11. At period 1 of the shock, the average capital of entrants is 0.6% higher than at period 0, because some would-be small entrants are choosing not to enter. By period 2, potential entrants with small optimal capital stock (i.e. with lower idiosyncratic productivity signals) are entering again due to the lower interest rate, which raises their expected value. Notice that after the one-period shock, the average capital of entrants falls just back to its pre-shock level. By contrast, the two- and five-period shocks lead to a drop to almost 1% less than the pre-shock level.
Figure 3.11: Total capital of entrants (top) and incumbents (bottom)
Figure 3.12: Employment by entrants (top) and incumbents (bottom)
In Figures 3.11-3.13, the capital, output and employment of entrants are defined as the optimal values for the next period (one period after entry), since entrants have to wait for one period to produce. This is why the capital of entrants drops immediately in response to the shock (the top graph in Figure 3.11), whereas overall capital responds with a one-period
lag (Figure 3.14 below).

The immediate responses of entrants to the uncertainty shock are much more pronounced than those of incumbents. For instance, the measure of entrants drops immediately by around 5.4%, while the total measure of firms drops only by about 0.4%, and the capital of entrants drops by about 5%, compared to a drop of only up to 1% by incumbents. The response of employment by entrants is negative while for incumbents the response is positive. The negative response for entrants is due simply to the reduced number of entrants, whereas incumbents replace some capital with labor in production. The total capital stock in the economy falls, both due to more firms choosing inaction because of the interaction of the capital adjustment costs with temporarily higher uncertainty, and due to the temporarily much lower capital of entrants. Since in normal times both entrants and exitors make up around 7 to 9 percent of firms, a large decrease in average entering capital together with a large decrease in the measure of entrants can have a significant effect on aggregate output. This effect is magnified by the fact that surviving young firms tend to grow quickly (Clementi et al. 2015), making up an increasing proportion of the total output over the first few years after their entry.

The disproportionate effect of the uncertainty shock on potential entrants is likely due in part to the form of the adjustment cost functions for entrants and incumbents. The strictly convex part of the adjustment cost function for incumbents is $c_q (k' - (1 - \delta)k)^2$, whereas for entrants it is $\gamma \frac{\kappa^2}{2}$. This captures the idea that large existing firms find it easier to make an adjustment of a given absolute value. It also makes it unlikely that an entrant will start out large – it would need a high productivity signal for that to be optimal. For a given productivity level, for most realized values of the state variables a smaller firm is at least as likely to exit than a larger one, as suggested by Figures 3.5 and 3.6 above. This causes some potential entrants to foresee that they will exit in the next period without ever having produced, thus making a negative payoff rather than the zero reservation payoff they get from staying out.
Figures 3.14-3.18 show the impulse responses of aggregate variables to a two-period uncertainty shock for both the baseline model (the one described in the earlier sections) and a model that is the same in all respects except that there is no entry or exit – firms do not need to pay a continuation cost and remain in the market even if their profits are temporarily negative. The differences in the magnitudes, and in the case of output the qualitative features of the responses, are striking.

Figure 3.14: Aggregate capital for baseline and no entry/exit economies
Figure 3.15: Aggregate output for baseline and no entry/exit economies
Figure 3.16: Employment for baseline and no entry/exit economies
Figure 3.17: Consumption for baseline and no entry/exit economies
Clearly, it makes a big difference whether entry and exit are allowed in the model. Consider first the impact of the uncertainty shocks on the model without entry and exit. This model is like that studied by Bloom et al. (2014) except that I do not include hiring frictions. The variables’ responses to an uncertainty can be divided into short-term and long-term responses. The initial effect of an unexpected high level of uncertainty is to raise employment. Labor replaces capital in production (see Figure 3.14 for capital and Figure 3.16 for labor) as higher uncertainty causes firms to become more reluctant to invest in capital. This is because firms face capital adjustment costs, but can hire and fire workers freely. Output also initially rises after the first period of high uncertainty (see Figure 3.15) because the convexity of profits in productivity makes firms on average initially want to produce more when uncertainty is high, as in the steady state experiments. Consumption initially rises as well, due to the higher output together with lower demand for savings, which makes
the return to savings fall. This is unlike in the model with price frictions of Basu and Bundick (2014), where consumers’ precautionary saving drives the economy’s response to an uncertainty shock. After the uncertainty shock ends and the uncertainty process returns to normal, some incumbent firms have pent-up demand for capital as described by Bloom et al (2014): They received good enough idiosyncratic productivity shocks so that they would have invested more had uncertainty not been high. Now those firms that continue to have good shocks under low uncertainty make up for past inaction by investing at a higher rate, and also by replacing labor by capital. Consumption then falls again briefly (Figure 3.17) because of the increase in investment and the added capital adjustment costs that are being paid. The decrease in the aggregate capital stock and in investment, shown in Figures 3.14 and 3.18, lead to a gradual decrease of aggregate output back to the pre-shock level, without ever falling much below this level (Figure 3.15).

By contrast, in the baseline model (with entry and exit), aggregate output drops to about 0.1% below its pre-shock value about 2 years after the initial onset of the shock. Investment and aggregate capital drop by much more, and total employment and consumption increase by less, compared to the no entry/exit economy. In addition to allowing the number of firms to vary, entry and exit alters the pre-shock distribution of firms with respect to capital and productivity. Because they can exit when they get a bad set of productivity shocks, firms are both larger and more productive on average in the pre-shock period of the baseline economy compared to the no entry-exit economy.

Bloom et al. (2014) mention that the misallocation of resources due to a rise in uncertainty is another important reason for the resulting economic downturn. In their paper, this misallocation results from firms “freezing” both hiring and investment after an uncertainty shock due to irreversibility and fixed adjustment costs, so that there are some units of labor and capital being used by less productive firms that would have been used by more productive firms in the absence of the shock. Here the entry and exit of firms allow for an additional type of misallocation: There are potential firms who do not enter, yet have higher produc-
tivity than some continuing firms. Figure 3.19 graphs the impulse-response function for the misallocation of labor, measured as the correlation between firms’ productivity and their share of labor.

![Graph showing misallocation of labor for baseline and no entry/exit models](image)

Figure 3.19: Misallocation of labor for baseline and no entry/exit models

### 3.5 Conclusions

This paper has studied the effects of increases in uncertainty – permanent and temporary, expected and unexpected – on an economy in which firms face both convex and non-convex costs of capital adjustment and can enter and exit the market endogenously. The incorporation of endogenous entry and exit into the model has significant effects on the responses of aggregate variables to an uncertainty shock. The long-term negative response of investment in the model with entry and exit contrasts with a relatively short negative response followed
by an overshoot in the model without entry or exit. The long-term responses of output in the
two models are qualitatively different, with a long period of output below the ergodic level
in the model with entry and exit, and an initial increase followed by a gradual decrease to
the ergodic level in the model without entry or exit. The differences between the models are
due to the life-cycle dynamics of firms in the baseline model. In this model, small firms and
potential entrants are the most negatively affected by an uncertainty shock. This creates a
missing generation effect, where firms that would have grown quickly without the shock are
absent from the market.


References


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