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Firm risk and leverage-based business cycles

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ABSTRACT

I characterize cyclical fluctuations in the cross-sectional dispersion of firm-level productivity. Using the micro-estimated dispersion, or "risk", stochastic process as an input to a baseline small-scale financial accelerator model, I assess how well the model reproduces cyclical movements in both real and financial conditions of the economy. In the model, risk shocks calibrated to micro data lead to empirically-relevant steady-state leverage, a financial measure typically thought to be closely associated with real activity. In terms of aggregate quantities, pure risk shocks in the small-scale general equilibrium model account for a notable share of GDP fluctuations — roughly 5%. The volatility of the risk process I measure using micro data is, remarkably, not very different compared to recent estimates of risk shocks based on medium- or large-scale models using macroeconomic data. These seemingly contrasting starting points for measuring risk shocks do not imply any dichotomy at the core of a popular class of DSGE financial frictions models. Rather, it is the particular transmission channels in financial-frictions models — whether small scale or medium scale — that are critical for aggregate quantity fluctuations to arise based on risk shocks.

1. Introduction

There are two distinct components of this paper that contribute to the literature on macro-financial accelerator models. The first is an estimation of time-series volatility of "risk shocks" using *microeconomic* data, and the second is an application of the empirical results to a well-known *macroeconomic* framework. The notion of "risk" studied is the standard deviation in any given time period of firm-level idiosyncratic productivity. "Risk shocks" are thus exogenous time variations in this cross-sectional dispersion. On the estimation front, the time-series volatility of idiosyncratic productivity risk is consistent with or a bit larger than other existing *microeconomic* estimates, and is on the same order of magnitude compared to recent *macroeconomic* estimates. Moreover, average productivity and the cross-sectional standard deviation of idiosyncratic productivity are highly countercyclical with respect to each other.

The estimation result leads to the second component of the study, which is a quantitative application to a small-scale general equilibrium financial accelerator framework. Two main results emerge here. First, the endogenous steady-state leverage ratio in the model nearly matches that in the data (0.67 vs. 0.56, respectively), even though the calibration was not designed to do so. Second, using the estimated time-series volatility of cross-sectional risk as a driving force of the model, risk shocks alone generate volatility in standard macro aggregates, such as GDP. Variance decomposition shows that nearly

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5% of GDP volatility is accounted for by risk shocks, and the rest is driven by total factor productivity. Given that these are the only two shocks in a small-scale model that, by changing just two parameters, nests the simple real business cycle model, 5% of GDP volatility accounted for by risk shocks is remarkable. Risk shocks also generate fluctuations in financial aggregates such as leverage and bankruptcy — about one-third of the variance in financial aggregates in the model is accounted for by risk shocks.

The empirical side of this paper itself consists of two different parts. First, I characterize fluctuations in firm-level dispersion using U.S. micro data for the period 1973–1988. Specifically, based on data constructed by Cooper and Haltiwanger (2006), I estimate the mean, the persistence, and the time variation in the cross-sectional dispersion of firm-level productivity. The estimates for the mean and persistence parameters are broadly similar to those in existing literature.

The estimated time variation, which is identified in this paper as risk fluctuations, can be compared to both existing *microeconomic* evidence and to recent *macroeconomic* estimates. The measure of firm risk I base on Cooper and Haltiwanger (2006) is strongly countercyclical with respect to GDP, consistent with the micro-level evidence of Bloom, Floetotto, Jaimovich, Saportka-Ekstein, and Terry (2012) — henceforth, BFJST (2012) — and Bachmann and Bayer (2013). In a microeconomic sense, firm risk is quite volatile over the business cycle: measured by the ratio of the standard deviation of *innovations* in risk to average risk, the volatility of annual firm risk is 17 percent. By this metric, volatility of firm risk is similar to that measured by BFJST (2012), but is substantially larger than that measured by Bachmann and Bayer (2013). Comparisons must be made with caution, because the U.S. micro data I examine are different from the U.S. micro data examined by BFJST (2012), which in turn are different from the German micro data examined by Bachmann and Bayer (2013). Nonetheless, the evidence I present complements these and other emerging empirical measures of firm-level risk. The estimated risk shock process is used as an input to the theoretical model.

Before proceeding to theory, though, the second empirical aspect is an extension of the leverage measure provided in Masulis (1988) to cover the time period 1973–1988, which has two advantages.[1] One advantage is to allow for clean comparability with the period over which the risk shock process is estimated. The other is that the Masulis-based leverage series also permits some comparability with a component of the Christiano et al. (2014) *macroeconomic* estimation, about which more is described soon.[2,3]

In terms of theory, I deploy the estimated risk shock process in the Carlstrom and Fuerst (1997) agency-cost "investment model". A closely-related existing study is Dorofeenko, Lee, and Salyer (2008) — henceforth, DLS — which also analyzes the importance of risk shocks in the Carlstrom and Fuerst (1997) model. The marginal contribution relative to DLS is the *estimation* of risk shock parameters rather than assumptions about them. The crucial risk-shock volatility parameter I *estimate* is an order of magnitude larger than their *assumed* parameter. Not surprisingly, the quantitative importance of risk shocks alone in generating fluctuations turns out be much larger in my results compared with the results in DLS.[4]

As described in Section 2, my estimated volatility of risk overstates the underlying shock to the variance by roughly a factor of two. Nevertheless, comparing my results to those of the prominent recent study by Christiano, Motto, and Rostagno (2014) — henceforth, CMR — my estimated volatility of risk is of the same order of magnitude. In a medium-scale model, CMR estimate, among a host of other parameters, a risk shock process based on *macroeconomic* data.[5] In contrast, my estimated risk shock process is based on *microeconomic* data. The details of my estimation are described in Section 2 and Section 5; but, to compare the results in a macro setting, my estimated volatility of the crucial parameter for cross-sectional risk is between 50% (as an upper bound) and 25% (as a lower bound) of the most comparable estimate in CMR. This result is surprising given the completely different approaches CMR and I use in estimating this crucial parameter.

Taken together, my results (which impose microeconomic discipline), the results of DLS, and the results of CMR (which impose macroeconomic discipline) may raise an issue about the "proper" way to parameterize risk shocks in agency-cost accelerator models — use of micro data vs. macro data. That is, the contrasting starting points for empirically measuring risk shocks seem to raise a tension between a micro-calibration approach and a macro-calibration approach. This tension does not have to be portrayed in a negative light. Rather, it indicates that further research is required.

Finally, two points regarding modeling approach are in order. First, as should be clear from the discussion so far, the idea of "risk shocks" in this paper is variations over time in the cross-sectional standard deviation of firm-level productivity, holding constant average productivity. This is the same notion of idiosyncratic "second-moment shocks" that BFJST (2012), Bachmann and Bayer (2013), CMR, and DLS study. However, it is distinct from an aggregate notion of "second-moment shocks" emphasized by Justiniano and Primiceri (2008), Fernández-Villaverde and Rubio-Ramirez (2007),

[1] I thank Ana Lariau for her tenacity in locating the data in the IRS Corporate Income Tax Returns database in order to be able to extend the Masulis (1988) series. The leverage data provided in Masulis (1988) ended in 1984.

[2] Leverage, defined as the debt-to-asset ratio, is often thought to play a central role in connecting financial and real activity. In principle, model-based leverage fluctuations have the potential to drive, or at least be associated with, real fluctuations. Such "leverage-based business cycles" could arise through fluctuations in firms' balance sheet conditions that are induced by risk shocks. The transmission channel that the model emphasizes and tests is thus explicitly financial: if there were no agency costs in financial markets, there is no channel by which risk shocks could affect real fluctuations at all.

[3] This is not to deny that there may be other channels by which risk shocks could affect real outcomes; for clarity in this paper, other channels are not being tested. This aspect of the model is similar to the qualitative business cycle model of Williamson (1987) and the quantitative models of Dorofeenko et al. (2008), Christiano et al. (2014), and others.

[4] Earlier versions of my paper used the Carlstrom and Fuerst (1998) "output model", in which the results are weaker than in the investment model. Section 5 discusses further.

[5] The CMR framework's starting point is the sticky-price financial accelerator model of Bernanke et al. (1999).