Research Statement

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I am a macroeconomist. My research asks how financial conditions, and monetary policy in particular, change the investment decisions of individual firms, and what those decisions mean for long-run growth. I work with large firm-level panels and dynamic econometric methods, and I build structural models to interpret what the data show. My current work is on innovation, the form of investment closest to technological progress and the most exposed to financing frictions.

Job market paper: Monetary Policy and Firm Innovation

Macroeconomists usually treat monetary policy as a short-run stabilization tool. A growing literature argues that it can also have persistent effects through investment and innovation. Most of that evidence is aggregate, and it leaves three questions open. Does monetary policy draw new firms into innovation, or does it change how much existing innovators invest? How does a change in R&D spending show up in the quantity and quality of what firms invent? And is the response symmetric across easing and tightening?

To answer them, I link Compustat financial data, USPTO patent records and CRSP market data at the firm level, with patent citations, the Kogan, Papanikolaou, Seru and Stoffman market value of patents and a text-based importance measure as the output side. Knowledge capital is built from R&D by the perpetual inventory method. The monetary policy shocks are the high-frequency series used by Ottonello and Winberry, 164 shocks from 1990 to 2007; the Great Recession is excluded because high-frequency identification stops working at the lower bound. I estimate the dynamic effects with local projections over twenty quarters, combined with Probit and Tobit models for the two margins of R&D investment.

The paper has four main findings. First, the R&D response operates almost entirely on the intensive margin. Expansionary shocks raise R&D and knowledge capital among firms that already innovate, and the response is an order of magnitude larger than on the extensive margin, which cannot be distinguished from zero at any horizon. Second, the composition of innovation output changes. After an expansionary shock, patent counts fall in the short run while citations, patent importance and the share of patents in the upper tail of the importance distribution rise over the medium run. Third, a two-stage analysis shows that this reallocation runs through the R&D response itself rather than through a direct effect of the shock on patenting. Fourth, the effects are asymmetric in sign. Contractionary shocks reduce both the quantity and the quality of innovation, and the reallocation toward quality is identified most cleanly among economically large shocks.

The results bear on three literatures. Work on monetary policy and heterogeneous firms sorts the investment response by leverage, liquidity, age and size. For innovation the split that matters most is simpler, whether a firm does R&D at all. Work on monetary policy and growth gets a firm-level channel, from the rate shock through R&D spending to the kind of patents firms produce. For innovation research, citation-based and text-based measures of patent quality rise after an expansionary shock while per-patent market value shows no reliable response, so a study's answer can depend on which proxy it uses.

Work in progress

Two coauthored papers ask which part of firm investment responds, first for AI adoption and then for physical capital.

Artificial Intelligence and Inventory Management: Evidence from U.S. Retail Industry (with Shuang Chen, Min Fang, Boyuan Li and Baolian Wang; draft available). Firms hold inventory, and working capital more generally, because they cannot forecast demand and supply exactly. AI lowers the cost of forecasting (Agrawal, Gans and Goldfarb, 2019), so we ask whether it changes how retailers manage working capital, and whether it helps them when a supply chain breaks. Firms do not report where they use AI, so we measure it from the near-universe of U.S. online job postings, Lightcast data from more than 40,000 sources over 2010 to 2023. We flag AI vacancies by their machine-learning skills and sort them into marketing and supply-chain jobs with a tiered keyword taxonomy that favors precision over recall, then link the measures to Compustat for more than 1,300 public firms.

In long differences over 2010 to 2023, rising AI adoption goes with a shorter cash conversion cycle for retailers, by about a week of receivables per standard deviation of supply-chain AI, and with essentially no change for other firms. The shortening comes from receivables. Days receivables outstanding falls for all seven AI measures we build, days inventory outstanding does not move in any specification, and days payables falls for two of the seven. Listed retailers had squeezed most of the slack out of inventory before our sample begins, so the customer side is where AI still had room to work. The second test treats the 2018 U.S.-China tariff announcements as a supply-chain shock, following the event-study design of Huang et al. (2023). We interact pre-shock China-import exposure, retail status and 2017 AI intensity, with buy-and-hold abnormal returns over 20 to 80 trading days as the outcome. China-exposed retailers with more supply-chain AI lost significantly less market value. The effect is zero on impact, shows up by about 40 trading days and keeps growing through 80, and it does not appear for marketing AI. Without the import-exposure control the sign flips, because AI-intensive retailers are also the larger and more import-reliant firms the tariffs exposed.

Solving the Macro and Micro Investment Elasticity Inconsistency with Incomplete Information (with Jonathan Adams, Min Fang and Eugenio Rojas; draft in progress). My job market paper finds that the innovation response to monetary policy runs through the intensive margin. For physical capital the margins have been debated for a long time. Heterogeneous-firm investment models cannot match two elasticities at once. One is the macro elasticity, how much aggregate investment responds to the real interest rate. The other is the micro elasticity, how firms move between the extensive and intensive margins. Fixed costs small enough to fit the micro evidence (Cooper and Haltiwanger, 2006; Khan and Thomas, 2008) leave aggregate investment far too sensitive to interest rates, and fixed costs large enough to fit the macro elasticity (Winberry, 2021; Koby and Wolf, 2020) distort the micro margins.

We think fixed costs alone cannot fit both, so we add incomplete information. Firms in our model pay fixed, partially irreversible and quadratic adjustment costs, and each sees only a noisy signal of its own productivity. I solve the model by value function iteration in Julia and compute the stationary distribution with the non-stochastic method of Young (2010), so the moments carry no simulation error. Starting from the Cooper-Haltiwanger and Khan-Thomas calibrations, we change only the volatility of the information noise. More noise dampens both the micro and the macro elasticity and narrows the gap between them, and in some calibrations it closes the gap.

Future research

All three plans ask which projects firms take up when financing changes, and what that does to productivity over time.

A model of the quality margin. The main empirical result of my job market paper is that easier financing moves research from incremental toward high-impact projects. I plan a heterogeneous-firm model in which firms choose between project types under financial frictions, and easier financing lowers the cost of long-horizon, higher-risk projects. With it I can ask how much of monetary policy's long-run effect on productivity comes from the direction of research and how much from its volume.

Why quality measures disagree. Citation-based and market-value measures of patent quality moved differently in my job market paper. I want to work out when the two diverge and what each one measures, since the answer matters for any study that uses patents to measure the returns to innovation policy.

Technology adoption and financial conditions. Combining the job-posting measures from the AI paper with the monetary policy shocks from my job market paper, I can test whether credit conditions change how fast firms adopt AI and in which parts of the firm.