Short-Term Shocks and Long-Term Investment

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July 2018

Preliminary & Incomplete: Do Not Cite Specific Results

Abstract

A little under half of the variance in shocks hitting firms appears to emanate from short-term, transitory sources. Forward-looking investment comoves substantially with these transitory shocks. Mistaken inference in analyses of firm investment will likely result from ignoring these patterns, which can in fact provide valuable discipline for a wide range of investment frictions. An estimated quantitative model incorporating these insights reveals that the sensitivity of long-term investment to short-term shocks causes substantial misallocation of capital and lost firm value.

*Thanks to participants at the ISIR program at the ASSA meetings, the Boston Area Macro Juniors Group, and the BU Macro Faculty Lunch. Thanks also to our discussant Robert Chirinko.

Shocks to profitability continually buffet firms which must choose their long-term investment in a range of productive assets at each moment. The choices faced by firms pose inherently dynamic tradeoffs, the sacrifice of resources in the short-term to provide for the long-term health of the firm's business. The resulting investment behavior of firms determines a great deal about the macroeconomy, affecting the severity and duration of recessions, the rate of long-term growth, and the overall efficiency of the allocation of resources across producers in the economy, highlighting the importance of careful research into dynamic firm investment behavior.

Such dynamic problems are not unique to firms, of course. Households choosing the amount of their income to save for the future, at a cost of lower consumption today, must navigate an environment filled with random events and shocks. For decades, dating back to at least Friedman (1957), economists have drawn an important distinction between two distinct types of shocks to households. In response to short-term, transitory shocks - for example, a one-off bonus payment from their employer - households in benchmark models shouldn't adjust their forward-looking consumption much at all. By contrast, off-the-shelf models predict that long-term, persistent shocks - for example, job loss resulting in unemployment - will cause households to retrench and cut their consumption substantially. Therefore, researchers studying the impact of factors such as financial constraints on household consumption behavior cannot think separately about frictions and the nature of shocks hitting firms. More concretely, an observed drop in consumption after an income shock would only be out of the ordinary or associated with financial constraints if the underlying shock was short-term in nature. The distinction between shocks with varying degrees of persistence, and the associated measurement and modelling agenda, has proven quite profitable for macroeconomics and labor economics over the past six decades (Blundell et al., 2008).

Remarkably, given the contrast posed by developments in consumption research, economists studying firm investment behavior have largely ignored the distinction between two different types of shocks. Such statements are of course not true in the strictest sense, with notable exceptions in the analysis of papers such as Gourio (2008) or Roys (2011). However, a prototypical example of quantitative research into firms starts with a persistent, long-term shock process for profitability, often a log AR(1) specification for exogenous firm-level TFP, inferring the presence and magnitude of firm investment frictions on the basis of this quite narrow view of the shocks firms face. Note that exactly the same qualitative insights from the household consumption literature carry over to the theory of firm investment. To fix ideas, Figure 1 plots the response to two distinct shocks which might hit a firm: short-term transitory shocks and long-term, persistent shocks.

Firms in benchmark models should respond strongly to long-term persistent shocks, e.g., the entry of a new competitor into their market or a permanent regulatory change, because these shocks affect the future payoff to their investment. But, by contrast, firms should ignore short-term transitory shocks that don't affect the expected future marginal product of capital, e.g., a

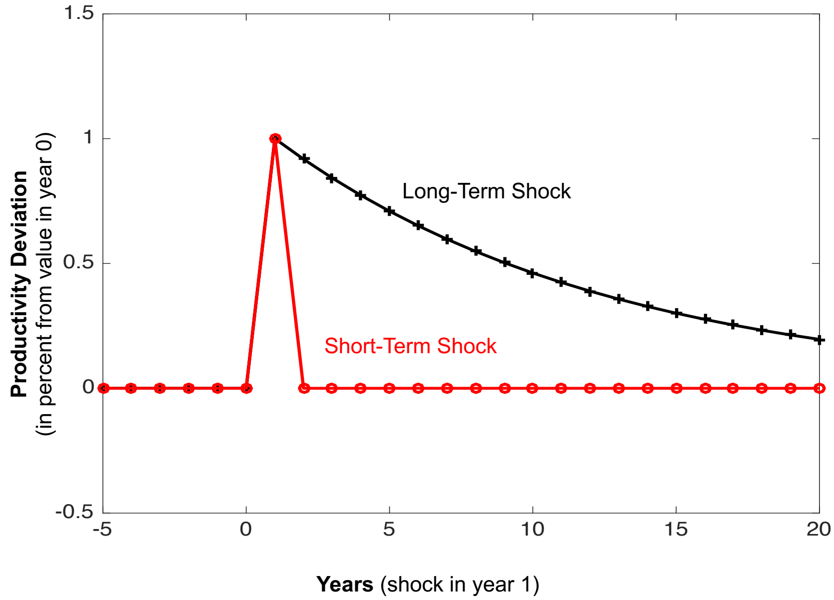

Figure 1: Two Different Profitability Shocks at Firms

Note: The figure plots the stylized impulse response of firm profitability or productivity to two distinct shocks. The response to a persistent, long-term shock is plotted in black with plus markers, while the response to a short-term, transitory shock is plotted in red with circles.

sudden weather event reducing today's revenues but not damaging productive capacity. The lesson is that comovement with or sensitivity of investment to short-term shocks reliably indicates some underlying friction and departure from benchmark models, while responses to persistent shocks do not. So the cursory attention paid to the firm shock process in much applied research may pose more than minor technical problems. In this paper, we argue that the nature of the shock process hitting firms, and the size and prevalence of short-term, transitory shocks, does in fact matter crucially for understanding firm investment.

We start by estimating a more flexible shock process for firm TFP in a panel of large US public firms over the last twenty five years, using a flexible likelihood-based panel estimator. We estimate that a large fraction, just under 40%, of the shocks faced by firms each period emanate from short-term, transitory sources. A cursory manual analysis of news articles and annual reports for some firms in our sample suggests that events such as reported consumer taste shifts, weather events, or firm reorganizations often occur simultaneously with short-term shocks, providing some texture on the potential underlying sources of firm shocks in this context. We then proceed to estimate the sensitivity of firm investment in tangible and intangible assets - that is, capital expenditures and R&D - to short-term shocks in our sample. We find substantial sensitivity of each form of investment to short-term shocks, consistent with underlying frictions causing a meaningful departure of firm investment behavior from simple benchmark models.

A natural question for investment research presents itself in light of these results: can applied researchers ignore the presence of short-term shocks in their research with little consequence? We emphatically answer no, for two distinct reasons. First, we demonstrate that ignoring short-term shocks in general leads to biased inference about fundamental values such as the persistence of long-term shocks or the level of adjustment costs in a given model. Second, on a more positive note, we highlight that the observed sensitivity of investment to short-term shocks provides a useful new target moment, offering empirical discipline for a range of investment frictions at firms, including financial constraints, information problems, or agency conflicts. Not only should researchers take care not to ignore short-term shocks, substantial value can be added by exploiting the extra information contained in the analysis of short-term shocks.

In the final step in our paper's analysis, we build a model of firm-level investment subject both short-term and long-term shocks to profitability. We extend this standard model in straightforward fashion to incorporate reduced-form frictions causing investment wedges or shifts in firm investment in the face of short-term shocks. Taking the model to the data, we complete an SMM estimation exercise, targeting the reduced-form evidence on short-term shock prevalence and sensitivity that we highlighted above. We uncover that sensitivity of investment to short-term shocks causes around 10% of observed investment fluctuations and results in a sizable loss of firm value of around half a percent per year, many billions of dollars of destroyed value due to capital misallocation.

Section 1 analyzes short-term shocks and investment sensitivity in the data. Section 2 lays out the relevance of short-term shocks for modeling firm investment. Section 3 builds and quantifies model of investment with short-term shocks and investment sensitivity. Section 4 highlights challenges for research in this area. Section 5 concludes. Appendixes provide more information on the data (Appendix A) and the model (Appendix B).

1 Short-Term Shocks in the Data

In this section, we start by describing a panel of US public firms, providing data on firm TFP, sales, and various forms of investment. We then estimate a flexible firm profitability process with short-term and long-term components using a Bayesian MCMC routine for panel data. Finally, we estimate substantial sensitivity of tangible and intangible investment at these firms to short-term shocks.

Table 1: Descriptive Statistics

	Mean	Median	Std. Dev.	Firm-Years
Sales	1638.051	490.13	2774.463	14,307
Assets	2018.263	460.905	4402.774	14,307
Book Value of Capital	692.4463	107.028	2344.58	14,307
Capital Expenditures	124.2281	20.7915	482.6052	14,216
R&D Expenses	64.69228	8.665	207.1067	8,698
SG&A Expenses	323.5185	81.34	647.3065	13,317
Advertising Expenses	63.73171	5.627	173.6911	4,604
Employees	9.4906	2.48	30.943	14,307

Note: The table reports basic descriptive statistics for several variables drawn from our Compustat panel of firms covering 1990-2013 at the firm-fiscal year level. All values except for the number of employees are reported in millions of US dollars, and number of employees is reported in thousands of people. The final column reports the number of non-missing firm-years in our sample for the indicated variable. The variable names are mostly self-explanatory, although SG&A expenditures refer to selling, general, and administrative expenses, and the book value of capital refers to the book value of the tangible plants, property, and equipment stock. Information is drawn from the annual reports of US public companies.

1.1 Data on US Public Firms

Our main dataset is a panel of US-listed public firms drawn from income and balance sheet statements at annual frequency in the Compustat Fundamentals Annual database. For a total of around 14,000 firm-fiscal year observations, spanning around 600 firms for the period 1990-2013, we use the following series: sales, tangible investment, employment, and several proxies for intangible investment: research and development expenses (R&D), selling, general, & administrative expenses (SG&A), and advertising. We also make use of a panel of revenue TFP computed by İmrohoroğlu and Tüzel (2014) for a smaller balanced panel of around 700 firm-fiscal years. [1] Table 1 provides descriptive statistics on our main sample of firms, which are large with around $1.6 billion in annual sales and 9500 employees on average.

1.2 A Flexible Profitability Process at Firms

We are interested in decomposing the shock process at firms into long-term, persistent and short-term, transitory components. We will refer to firm shocks as profitability shocks, in principle including variation in supply-side factors such as firm-level TFP as well as demand shifters. For

[1] İmrohoroğlu and Tüzel (2014) estimate revenue TFP for a balanced panel firms relying on tangible capital and labor inputs with elasticities estimated using the Olley and Pakes (1996) control-function approach.

firm j in year t, let profitability z_{jt} be given by the sum of two stationary processes

$$z_{jt} = \varepsilon_{jt} + \nu_{jt}. \tag{1}$$

Here ε_{jt} is a persistent "long-term" AR(1) process

$$\varepsilon_{jt} = \rho\varepsilon_{jt-1} + \eta_{jt}, \quad \eta_{jt} \sim N(0, \sigma_\eta^2),$$

where the parameter $\rho \in (0, 1)$ governs the autocorrelation of the long-term shock and σ_η^2 is the variance of the persistent long-term innovation. The second component of firm profitability, ν_{jt}, is a transitory i.i.d. short-term shock following

$$\nu_{jt} \sim N(0, \sigma_\nu^2).$$

When $\sigma_\nu^2 = 0$, the profitability process in Equation (1) takes an AR(1) form which has become the traditional specification for idiosyncratic firm-level TFP shocks in the firm dynamics, corporate finance, and macroeconomics literatures. However, when $\sigma_\nu^2 > 0$, the process exhibits richer dynamics, crucially allowing for large or small predicted changes to future conditions at a firm after a shock today.

1.3 Bayesian Estimation of Short-Term Shocks

Moment-based or likelihood-based methods can be used to estimate the shock process in Equation (1). In the final section of this paper, we'll rely on moment-based methods within the context of a fully specified structural model of firm investment to estimate the shock process at firms. However, before specifying the model, we first explore our data in a purely reduced-form investigation. In this context, since the shock process admits a linear Gaussian state-space representation, likelihood-based estimation is feasible. We follow a Bayesian estimation approach introduced in Nakata and Tonetti (2015). The associated MCMC posterior sampler, detailed more in Appendix A, tends to have strong finite-sample properties in the panel setting relative to the traditional maximum-likelihood estimator.

1.4 Estimated Short-Term Shock Volatility

We estimate the firm shock process in (1) using two distinct proxies for firm profitability. The first, measured log revenue TFP from İmrohoroğlu and Tüzel (2014), is a likely agglomeration of supply and demand-side forces that at least notionally approximate the driving process in most canonical firm-level models. The second series we consider is the log of sales at the firm level.

Table 2: Estimated Firm Shock Process

	Productivity	Sales
LT Persistence ρ	0.9152 (0.8777, 0.9506)	0.8810 (0.8735, 0.8883)
LT Volatility σ_η	0.2236 (0.1993, 0.2486)	0.2472 (0.2437, 0.2507)
ST Volatility σ_ν	0.1740 (0.1532, 0.1960)	0.0680 (0.0643, 0.0722)
Fixed Effects	Year, Ind.	Year, Firm
Years	2000-2013	1990-2013
Firms	50	597
Firm-Fiscal Yr. Obs.	700	14,328
ST Cond. Variance $\sigma_\nu^2/(\sigma_\eta^2+\sigma_\nu^2)$	38%	7%

Note: The table reports posterior median estimates (and 95% credible intervals) from the Nakata and Tonetti (2015) sampler. The middle column labelled "Productivity" uses the log of TFP estimated by İmrohoroğlu and Tüzel (2014), and the right column labelled "Sales" uses log sales. The MCMC uses 15,000 draws with 3,500 burn-in draws. The bottom panel reports the short-term variance share.

The TFP process is more directly linked to the underlying model driving process, but the sales series requires fewer assumptions for calculation and provides a distinct set of insights. Both sets of estimates are derived from well behaved MCMC routines.[2]

The middle column of Table 2 reveals that the shock process estimated from firm TFP at large US public firms exhibits a substantial transitory component. The standard deviation of the short-term shock ν_{jt} is 17% per year, comparable to 22% for the persistent innovation η_{jt} and accounting for around 40% of the total variance of TFP innovations each year. At the same time, the persistence ρ of the long-term component is equal to 0.91. Compared to estimates of the more traditional univariate AR(1) driving processes estimated from Compustat and comparable databases in the literature in firm dynamics, which are summarized in Appendix Table 1, the persistence of the long-term shock component is quite high. This differentiation would naturally

[2]See Figures A.1-A.2 in Appendix A for the diagnostics on the MCMC routines, which demonstrate that the posterior sampling procedures converge.

be expected if the true underlying process was given by (1), since the overall autocorrelation of observed firm profitability - averaged over short-term and long-term shocks - would be lower than the true autocorrelation of the persistent component of firm TFP.

The right column of Table 2 reports estimates of the process (1) applied to a panel of firm log sales. In this sample, short-term shocks account for a smaller fraction of the variance, just under 10%, of all the shocks hitting firms. Compared to the results for TFP, there is a major conceptual difference at work here. Crucially, the sales process at firms combines any underlying shocks faced by firms - including presumably exogenous shocks of the type we desire to understand - with any endogenous responses of firms to those shocks which also affect sales. Below we argue that firm investment appears to comove with short-term shocks. So if, say, a negative short-term shock caused a firm to cut its investment, fewer productive assets in future periods would reduce sales in the future. From the perspective of our estimation routine such a shock would appear to be persistent, i.e., long-term rather than short-term in nature, an effect which would be expected to bias downwards our estimate of the true underlying importance of short-term shocks. For our purposes the second column of Table 2, which is drawn from a much larger sample than the TFP estimates and requires fewer measurement assumptions, will prove useful for us later as an endogenous target moment in a structural analysis. However, the estimates are likely a sharp underestimate of the true prevalence of short-term shocks for firms.

1.5 Anecdotal News Analysis of Firms

Because our goal is to argue for the existence and importance of a previously little emphasized shock process at work at firms, we bear the burden of demonstrating that our statistical description of firm shocks in (1) links to some plausible variation in reality. We exploit the fact that the estimation procedure we use yields smoothed estimates of short-term shocks at firms. In particular, since a Kalman smoother underlies the likelihood-based estimation process above, we possess smoothed posterior estimates $\{\hat{\nu}_{jt}\}_{j,t}$ of short-term shocks for each firm j and year t.[3]

Our eventual goal is to exploit a large textual database drawn from news reports and annual statements of this sample of public firms to verify the plausibility of the link between the estimated transitory shocks and some coherent set of underlying events at firms. As a first anecdotal step towards that analysis, we have drawn out a small number of firms in our sample, manually examining news reports from the Factiva database as well as their annual statements. The result is a series of Appendix Figures A.3-A.5 that display sample paths of estimated short-term shocks, labelled with the timing of particularly meaningful events at these firms. As the figures

[3]Technically, these estimates are the median of posterior sampling draws of the smoothed series ν_{jt} from the Nakata and Tonetti (2015) sampling procedure.

indicate, large short-term innovations appear to be clustered during periods in which firms report demand or taste fluctuations, experience severe weather events or disasters, or experience CEO turnover. This preliminary analysis gives us some comfort both that our statistical description of firm risk in (1) links to true underlying fundamental variation at firms but also that such variation is intuitively linked to events of a transitory, short-term nature.[4]

1.6 Investment Sensitivity to Short-Term Shocks

Our analysis so far suggests that short-term shocks appear to buffet firms each period. In a wide class of simple dynamic firm investment models with time-to-build, absent any other frictions firms would optimally ignore short-term shocks entirely in their investment decisions. Since such shocks don't affect the expected future marginal product of capital, shifting long-term forward looking investment today would result in misallocation. Given this frictionless benchmark of zero responsiveness, the extent to which long-term or forward-looking investment does in fact comove with short-term shocks yields insight into the nature of underlying frictions, such as financial constraints, information frictions, agency conflicts, or other factors that may be at work at firms.

We therefore estimate a series of simple sensitivity regressions of the form

$$x_{jt} = f_j + g_t + \beta_x \hat{\nu}_{jt}^{sales} + \epsilon_{jt}, \tag{2}$$

where x_{jt} is some measure of firm investment and $\hat{\nu}_{jt}^{sales}$ is the smoothed estimate of transitory shocks at firms from our panel of the log of firm sales. Above, f_j and g_t are a full set of firm and time dummies, and β_x is the coefficient of interest indicating the observed comovement or sensitivity of investment x to short-term shocks. Table 2 displays the sensitivity estimates for tangible capital investment, R&D, broad intangible spending in SG&A, advertising, and employment. The dependent variable in each case is $x_{jt} = IHS(X_{jt})$, where X_{jt} is the raw level of the spending indicated in the column header and "IHS" refers to the inverse hyperbolic sine, a transformation equivalent to the natural log to a first order but defined at zero and negative values. Since the underlying process z_{jt} in our panel of firms is log sales, the resulting coefficients can be interpreted as elasticities.

Each of these forms of investment - tangible and intangible, relating to both capital and labor - exhibits substantial sensitivity or comovement with short-term shocks, consistent with a departure

[4]In reality, an underlying description of firm risk would link discrete events to some fundamental innovations that might have both short-term and long-term impacts. In other words, a given event such as a CEO departure may have both some short-term impact - the disruption to the firm - as well as a long-term impact - due to, say, a new strategy by an incoming executive. Nothing about the shock process or the economic arguments we entertain here is incompatible with the commingling of horizons of impact within a single discrete event.

Table 3: Estimated Investment Sensitivity

Dep. Var.	Cap. Inv.	R&D	SG&A	Advertising	Employment
ST Shock	10.92***	5.32***	6.82***	9.41***	6.84***
$\hat{\nu}_{jt}^{sales}$	(0.56)	(0.64)	(0.34)	(0.90)	(0.41)
Fixed Effects	Firm, Yr.	Firm, Yr.	Firm, Yr.	Firm, Yr.	Firm, Yr.
Years	'90-'13	'90-'13	'90-'13	'90-'13	'90-'13
Firms	597	373	582	347	594
Firm-Fiscal Yr. Obs	13,928	7,644	13,049	4,509	14,016

Note: *,**,*** denote significance at the 10, 5, and 1% levels, respectively, with standard errors clustered by firm in parentheses. "IHS" is the inverse hyperbolic sine, $IHS(x) = ln(x + \sqrt{(1 + x^2)})$, defined over the reals and equal to $ln(2x)$ to a first order for positive x. The coefficients are therefore in elasticity units. The value $\hat{\nu}_{jt}$ is the smoothed posterior median transitory shock for firm j in fiscal year t from MCMC sampling using the Nakata and Tonetti (2015) estimator. Cap. Inv. refers to capital expenditures on plants, property, and equipment. R&D refers to expenditures on research and development. SG&A refers to selling, general, and administrative expenditures. Advertising refers to marketing expenditures. Employment refers to total employment in the firm. All values drawn from annual firm statements as reported in Compustat, and all regressions performed at the firm-fiscal year level.

from an underlying frictionless firm investment model.[5]. We defer a discussion of the magnitudes to our structural analysis below, but note that these sensitivity regressions link to a long literature on investment-cash flow regressions in empirical corporate finance (Fazzari et al., 1988; Kaplan and Zingales, 1997). A central endogeneity challenge in that literature is the potential correlation of current cash flows with unobserved investment opportunities. In the language of our analysis, today's cash flows are correlated with the persistent component of firm shocks ε_{jt}. By construction, the transitory short-term shocks ν_{jt} in our shock process are orthogonal from factors affecting the firm in future, so the regressions in (2) tackle this challenge directly and provide qualitatively new evidence on investment sensitivities at firms.

2 The Importance of Modelling Short-Term Shocks

Below we will lay out and estimate a fully specified model of firm investment subject to short-term and long-term shocks as well as a set of frictions generating sensitivity of investment to the short-

[5]Clearly, there is a generated regressor being exploited here, implying a likely downward bias in the traditional clustered standard errors. However, these estimates serve as target moments for structural estimation of a dynamic firm investment model later, where the sampling variation associated with the two-step estimation procedure is incorporated into estimation of identical estimates from simulated firm-level data.

term shocks. However, we first pause and emphasize the importance of accounting for short-term shocks for researchers working with models of firm dynamics and investment. Our discussion will take place in two parts. In the first, we emphasize the pitfalls of ignoring short-term shocks, i.e., a set of incorrect inferences that are likely to arise if a researcher follows the common approach of assuming a univariate AR(1) shocks process when firm shocks are actually described by the process (1). In the second part, we strike a more positive note, emphasizing the useful information embedded in the investment sensitivity to short-term shocks from Table 3 and arguing that such sensitivities provide a practical and informative new set of targets for applied researchers studying firms.

2.1 Incorrect Inference without Short-Term Shocks

Common practice in the literature on firm dynamics and firm investment is to assume that fundamentals at firms evolve according to a univariate AR(1) shock process. If the true data generating process is given by (1), then a researcher is likely to make systematically biased inference.

First, because the persistence parameter estimated in the misspecified process will rely upon the empirically observed autocorrelation of the sum of short-term and long-term shocks, the estimated value of this parameter will in general be biased downwards. Since in a wide class of investment models - for example, any Q-theoretic model of investment following along the lines of Hayashi (1982) - the persistence of a given shock directly maps to the magnitude of an investment response, such misspecification is likely to severely impact the accuracy of a given model's predictions.

Second, if a researcher uses a Q-theoretic model of investment - or any model of investment with convex adjustment costs as a key quantitative friction - then inference of the magnitude of adjustment costs is usually directly tied to the observed investment volatility and the comovement of investment with firm cash flows in any moment-based estimation approach. Figure 2 plots the observed investment volatility observed in simulated data in a model of investment subject to convex adjustment costs but no other frictions when the underlying shock process is given by (1).[6] Moving along the horizontal axis, we change the relative magnitude of short-term versus long-term shocks to firm profitability, changing no other parameters including, crucially, the adjustment cost parameter in the underlying model. A researcher ignoring the presence of short-term shocks and observing a given level investment volatility will in general infer an upward-biased estimate of adjustment costs. The magnitude of the over-estimation problem will increase with the presence of short-term shocks. Intuitively, the researcher would believe that low investment volatility is caused by an adjustment friction, when in reality firms simply would prefer not to respond to

[6] The underlying details of the model are provided in Appendix B, but at its core the model is a simple Q-theoretic investment problem with a modification to decreasing returns.

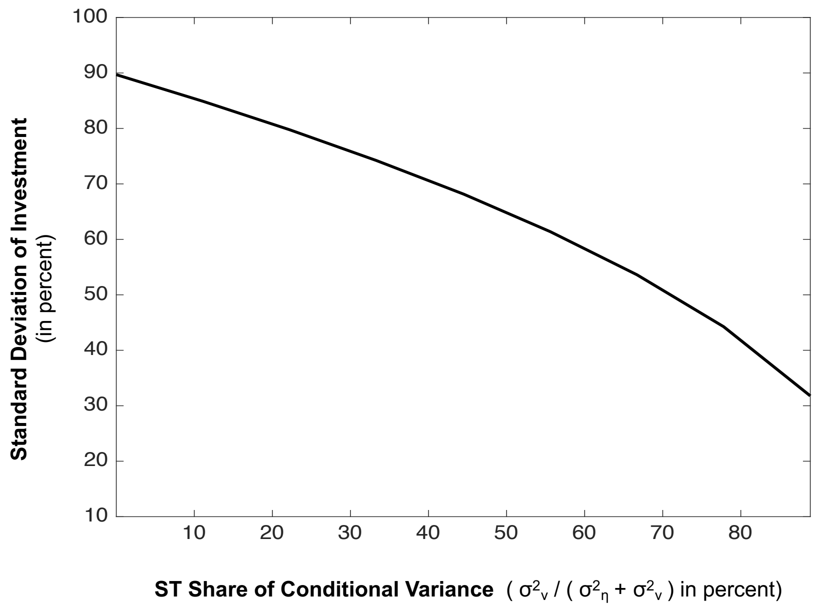

Figure 2: Investment Volatility in a Model with Short-Term Shocks

Note: The figure plots the standard deviation of investment observed in simulated data in a benchmark model of firm investment laid out in Appendix B. The parameterization of the model is held fixed for almost all parameters in the model, while the relative contribution of short-term shocks to the variance of profitability shock innovations faced by the firm is varied on the horizontal axis.

short-term shocks even in the absence of such frictions.

So, to summarize, applied researchers working with a workhorse class of firm investment models but ignoring the possibility of short-term shocks are likely to systematically underestimate the persistence of long-term shocks and overestimate the prevalence of adjustment frictions. Each of these errors would filter through to the rest of the researcher's inference about the firm, as well as a wide range of counterfactuals. Given the wide variety of papers using a framework based on the structure in Hayashi (1982) - see Eberly et al. (2008) for a survey - we view these mistaken inference problems as quite significant.

2.2 A New Target for Investment Models

Above, we argued that short-term shocks pose a challenge for inference for researchers ignoring them. But do these shocks offer any opportunities for new insights, i.e., is there an upside for firm investment research? Our answer, most decidedly, is yes. Consider three broad classes of investment frictions: financial constraints, information problems, and agency conflicts. We argue that the presence of short-term shocks, and crucially the sensitivity of investment to short-term

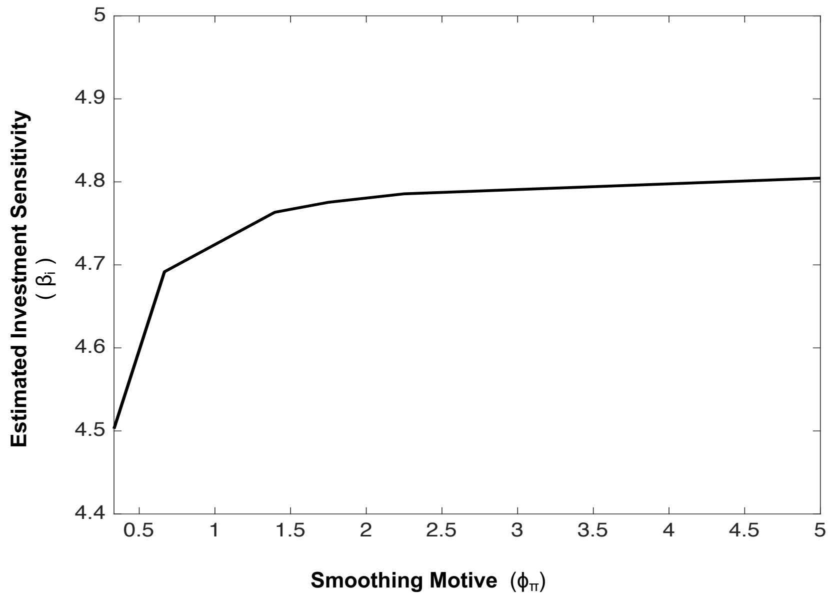

Figure 3: Investment Sensitivity in a Model with Financial Frictions

Note: The figure plots the estimated sensitivity of investment to short-term shocks, the analogue of the sensitivity of investment estimates in Table 3, computed from simulated data of a model of financial frictions laid out in Appendix B. The financial friction is a dividend or profit smoothing incentive varying positively with the parameter ϕ_π which varies along the horizontal axis.

shocks, offers a novel and valuable new target for quantifying each of these frictions.

First, consider models of financial frictions. These models take various forms, ranging from detailed corporate finance structures as in Hennessy and Whited (2007) to more macro-targeted implementations as in Jermann and Quadrini (2012). The key insight for our purposes is that models of financial frictions almost universally predict that such frictions generate more responsiveness of firm investment to transitory shocks when the underlying friction becomes more severe. In particular, firms facing transitory shocks have less ability to self-finance to fund investment, often leading to positive comovement of the investment flows and the transitory shocks even though after a short-term shock the future expected marginal product of capital remains constant. In Appendix B, we lay out a structure with dividend smoothing motives. As Figure 3 demonstrates, as the dividend smoothing motive or financial friction becomes more severe - moving from left to right on the horizontal axis - the estimated sensitivity of investment to short-term shocks, the equivalent of our figures from Table 3 run on simulated data, increases. Therefore, the investment sensitivity offers an attractive new moment for disciplining this class of models. We emphasize that the predictions of financial frictions models about the responsiveness of investment to persistent or long-term shocks is more muddled and often varies with the details of the financial friction itself.

By contrast, investment sensitivity to short-term shocks is a more robust prediction of financial frictions frameworks, underlining the utility of the sensitivity matching approach we advocate.

Second, consider models of information problems, e.g. David et al. (2016). In those models, firms typically don't have perfect information about the nature of the shocks they face in a particular period, often due to the presence of noise or transitory variation in firm outcomes. When firms have poor information, they may overreact to transitory shocks which are perceived to include some persistent component, and so the sensitivity we measure of investment to transitory shocks yields a similarly crucial target moment for this class of investment theories.

Third, consider models of agency conflicts that generate short-term oriented compensation structures - options compensation, nonlinear performance-based bonuses, rewards for meeting or beating benchmarks, etc... - for managers. In quantitative versions of these models (Terry, 2017), managers choosing investment subject to adverse short-term shocks may often cut their investment to maintain a given level of reported or short-term performance. The result is an increase in observed investment sensitivity to short-term shocks, again offering a crucial target moment for this class of models.

The overarching lesson from each of these examples is that short-term shocks offer both a challenge and an opportunity for investment researchers. While researchers ignore transitory shocks at their peril, the new empirical pattern of investment comovement with short-term shocks can discipline a wide variety of investment frictions at firms, crucial for understanding the role of such frictions in driving misallocation, business cycle amplification, and changes in firm value.

3 Misallocation from Short-Term Sensitivity in an Estimated Model

We have argued that the presence of short-term shocks and investment sensitivity offer new discipline for a range of investment frictions potentially generating misallocation or other other phenomena of interest to macroeconomics. One natural way to build upon this insight would be to pick a particular friction of interest, tailor the empirical strategy to that context, and build a narrow model focused on the link between investment and that single particular mechanism. Although such a path forward would be entirely defensible, we now take a distinct approach.

We build a fairly standard and general dynamic model of firm investment in partial equilibrium, with firms operating decreasing returns technologies subject to idiosyncratic shocks and convex adjustment costs. We depart from this conventional framework in several important ways. First, we model firm shocks as following the short-term plus long-term process given in equation (1). Second, given the evidence from Table 3 suggesting sensitivity of both tangible and intangible investment to short-term shocks, we allow for an intangible capital input in addition to a standard tangible capital input, with a flow of R&D investment into the stock of this intangible factor, say organizational capital. While sensible in light of our evidence above, neither of these changes implies that investment will comove with transitory shocks. So in a third addition to the model we build in reduced-form frictions, shifting the perceived investment price for firms as a function of the transitory shock faced by a firm. Mechanically, therefore, these perceived short-term investment price changes induce investment wedges at the firm which vary across firms and time as a function of short-term shocks. We view the resulting investment wedges as a quite general substitute for a range of potential micro-founded investment frictions like the ones considered in Section 2.

3.1 A Model of Reduced-Form Investment Sensitivity

We present the stationary model in recursive form, dropping time and firm subscripts for clarity. A firm's profitability shock process z follows

$$\log z = \varepsilon + \nu,$$

where just as in equation (1) the long-term ε and short-term ν shocks follow

$$\varepsilon = \rho\varepsilon_{-1} + \eta$$

$$\eta \sim N(0, \sigma_\eta^2), \quad \nu \sim N(0, \sigma_\nu^2)$$

where $0 < \rho < 1$ and $\sigma_\eta^2, \sigma_\nu^2 > 0$. The firm's output y is given by a decreasing returns to scale technology depending upon the profitability shock z, a tangible capital stock k, and an intangible or organizational capital stock o:

$$y = zk^{\alpha_k}o^{\alpha_o},$$

where $\alpha_k + \alpha_0 < 1$. Each form of capital accumulates according to time-to-build constraints as a function of tangible investment i and intangible investment - or R&D - x with

$$k' = (1 - \delta_k)k + i, \quad o' = (1 - \delta_o)o + x$$

where $0 < \delta_k, \delta_o < 1$. Firms face convex adjustment costs of each form of investment given by

$$AC_k(k, i) = \phi_k \left(\frac{i}{k}\right)^2, \quad AC_o(o, x) = \phi_o \left(\frac{x}{o}\right)^2.$$

In addition to these physical factors, the managers or decisionmakers at firms face reduced form costs of investment scaling with transitory shocks and given by

$$\nu \left(\tau_i \frac{i}{k} + \tau_x \frac{x}{o} \right).$$

When $\tau_i = \tau_x = 0$, these shocks do not affect the firm's investment problem. However, when τ_i or τ_x is negative, the associated investment flow will be perceived as more costly in the presence of negative transitory shocks, inducing a drop in investment. We model the reduced-form investment frictions as non-pecuniary, to avoid mechanical resource effects from the induced investment shifts. Managers, who discount the future at an exogenous real interest rate satisfying $0 < r < 1$, solve the dynamic optimization problem given by

$$V^M(\varepsilon, \nu, k, o) = \max_{i,x} \left\{ \begin{array}{c} y - p_i i - p_x x \\ -AC_k(k,i) - AC_o(o,x) \\ -\nu \left(\tau_i \frac{i}{k} + \tau_x \frac{x}{o} \right) \end{array} + \frac{1}{1+r} \mathbb{E} V^M(\varepsilon', \nu', k', o') \right\}. \tag{3}$$

The associated optimal investment policies $i^*(\varepsilon, \nu, k, o)$ and $x^*(\varepsilon, \nu, k, o)$ imply a fundamental firm value function - absent the non-pecuniary transitory costs - given by

$$V(\varepsilon, \nu, k, o) = \left\{ \begin{array}{c} y^* - p_i i^* - p_x x^* \\ -AC_k(k,i^*) - AC_o(o,x^*) \end{array} + \frac{1}{1+r} \mathbb{E} V(\varepsilon', \nu', k', o') \right\}. \tag{4}$$

We always operate on equation (3) when solving for firm behavior but compute value implications using equation (4). We numerically solve the manager optimization problem in (3) - which is a well behaved and tractable dynamic programming problem - using policy iteration, and Appendix B provides more details on the solution method used here.

3.2 Taking the Model to Data on Short-Term Shocks and Sensitivity

To quantify the model and infer the impact of short-term shocks and investment sensitivity, we must fix the value of the model parameters. We proceed in two steps, first externally fixing the value of several conventional parameters - including the real interest rate and depreciation rates - at standard values. We then estimate the value of the remaining parameters to match a set of target moments directly linked to our discussion above, in an overidentified SMM exercise.

First, we describe the externally fixed parameters. We choose $r = 4\%$ for an annual frequency, $\delta_k = 0.1$ to be comparable to conventional parameterizations, and $\delta_o = 0.2$ to match evidence on intangible capital depreciation rates from Li and Hall (2016).

Table 4 lists the remaining 9 estimated parameters, which we estimate via SMM by targeting

Table 4: Estimated Parameters & Targets

Parameters	Role	Parameters	Role
ρ, σ_η, σ_ν	Firm risk	ϕ_k, ϕ_o	Adjustment costs
τ_i, τ_x	Inv. sensitivity	α_k, α_o	Revenue elasticities

Moments	Explanation	Number
Cov(y, i, x)	Covariance of sales, investment, R&D	6 moments
$\hat{\rho}^{sales}$, $\hat{\sigma}_\eta^{sales}$, $\hat{\sigma}_\nu^{sales}$	LT/ST process estimates from sales	3 moments
$\hat{\beta}_i$, $\hat{\beta}_x$	Reduced-form investment sensitivities	2 moments

Note: The top panel of the table lists the parameters that are estimated to match the target moments in the bottom panel of the table.

the 11 moments also reported in the table.

Note that some of the estimated parameters - including the capital elasticities and convex adjustment costs parameters - are quite standard. We naturally include a range of conventional target moments, namely the covariance matrix of firm sales y, investment i, and R&D x. However, the other parameters govern the short-term/long-term profitability process $(\rho, \sigma_\eta, \sigma_\nu)$, as well as the sensitivity of investment to short-term shocks (τ_i, τ_x), and require additional information to provide empirical discipline. As target moments, we include the estimates $(\hat{\rho}^{sales}, \hat{\sigma}_\eta^{sales}, \hat{\sigma}_\nu^{sales})$ from application of the Nakata and Tonetti (2015) estimator to a panel of simulated firm log sales, i.e., the second column of Table 2 above. We also include the estimated sensitivities of tangible and R&D investment to smoothed short-term shock estimates from Table 3.

When applying an SMM estimation procedure like this, we face the responsibility of discussing the identification of the estimated parameters. In general, all of the moments contain information for all of the estimated parameters, but nevertheless certain moments provide particularly influential information for the estimation of some of the model's parameters. On the basis of comparative static exploration, we summarize these mappings briefly here. The volatility of firm output and its covariance with each of the forms of investment provides crucial discipline on each of the production elasticities α_k and α_o. The volatility of each investment flow, together with their covariances with output, provide discipline on the adjustment costs parameters ϕ_k and ϕ_o. Given other moments, the sales process estimates map fairly straightforwardly to the underlying TFP shock process estimates ρ, σ_η, and σ_ν. Finally, the estimated investment sensitivities link naturally to the reduced-form investment wedges τ_i and τ_x, in a manner demonstrated in Figure 4, which plots the implied investment sensitivity estimates from simulated model data as a function of the underlying sensitivity friction parameters.

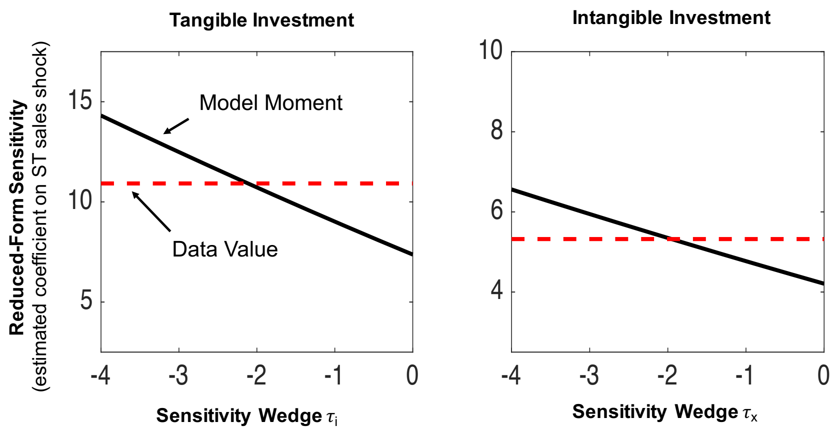

Figure 4: Identification of Investment Sensitivity Frictions

Note: The figure plots the estimated sensitivity of tangible investment (left panel) and intangible investment (right panel) to short-term shocks in simulated data from model parameterizations with various levels of reduced-form sensitivity parameters τ_i and τ_x on the horizontal axis.

Table 5 reports the model fit, a comparison of the estimated model and data moment values. Although the estimation is overidentified, and an exact fit can't be anticipated, the volatilities, sensitivities, and estimated sensitivities in the model are nicely comparable to their empirical counterparts, giving us some confidence in the quantitative implications of the model.

Table 6 reports the resulting point estimates of the model parameters.[7] Firms in this sample exhibit decreasing returns, with a higher share of intangible than tangible capital input and positive adjustment costs for each investment flow. The profitability shock process estimates indicate a high fraction - around 40% - of the total variance in profitability innovations emanates from short-term shocks, while the persistence of the long-term process is high at around 0.9. The negative values of the reduced-form investment friction parameters τ_i and τ_x induce positive comovement of each form of investment with transitory shocks. Therefore, not only do short-term shocks appear large, they appear to matter for firm investment.

Note that compared to the reduced-form estimates in Table 2, the profitability shock process estimates here are comparable to the results from the panel of estimated TFP in the data but exhibit higher short-term shock prevalence than the estimates based on firm sales. The underlying intuition for the difference is that in the presence of positive investment sensitivity to short-term shocks, a transitory impulse is propagated forward into capital and hence output tomorrow, implying that the shock appears artificially persistent when measured through sales alone. In other words, there's a key endogeneity issue at work here. Although using a panel of sales allow for a

[7]Standard errors are currently absent but in progress.

Table 5: Estimated Model Fit

Description	Data	Model
Est. LT persistence $\hat{\rho}^{sales}$	0.8810	0.9093
Est. LT volatility $\hat{\sigma}_{\eta}^{sales}$	0.2472	0.2170
Est. ST volatility $\hat{\sigma}_{\nu}^{sales}$	0.0680	0.0726
Est. Inv. sensitivity $\hat{\beta}_i$	10.920	12.480
Est. R&D sensitivity $\hat{\beta}_x$	5.3220	5.4453
Std. Deviation of Sales	0.5619	0.5493
Std. Deviation of Inv.	0.7660	0.7427
Std. Deviation of R&D	0.6393	0.4360
Corr(Sales, Inv.)	0.6342	0.6633
Corr(Sales, R&D)	0.5535	0.8858
Corr(Inv., R&D)	0.5055	0.8915

Note: The table above reports the value of each targeted moment drawn from Compustat data over 1990-2013 (middle column) and a panel of simulated firms of identical size in the best fit model (right column). The first three rows report the estimated sales process parameters computed as posterior medians applying the MCMC sampler proposed by Nakata & Tonetti (2015) to sales data after removal of firm and year effects. The next two rows report estimated sensitivities of tangible capital investment and R&D investment to smoothed posterior estimates of transitory shocks $\hat{\nu}_{jt}$ from the sales process estimation. The final six rows report the covariance matrix of the inverse hyperbolic sine (asymptotically log) of sales, tangible capital investment, and R&D investment, transformed to standard deviation and correlation units and computed after time and firm fixed effects.

Table 6: Estimated Parameters

Parameters	Description	Value
ρ	LT persistence	0.9178
σ_η	LT volatility	0.1642
σ_ν	ST volatility	0.1272
τ_i	Inv. sensitivity	-2.9960
τ_x	R&D sensitivity	-2.1622
ϕ_k	Inv. AC	0.4628
ϕ_o	R&D AC	1.3960
α_k	k elasticity	0.3419
α_o	o elasticity	0.4107
ST Cond. Variance $\sigma_\nu^2/(\sigma_\eta^2+\sigma_\nu^2)$	37.5%	

Note: The top panel of the table above reports parameter values in our best fit firm investment model. The parameters were chosen to minimize the sum of squared percentage deviations between a set of moments computed from our baseline Compustat sample over 1990-2013 and a simulated panel of firms in the model of identical size. The minimization was performed using a genetic algorithm, a type of stochastic global optimization routine. The bottom panel reports the share of conditional variance accounted for by the transitory ST in our best fit model.

much wider sample size and fewer measurement assumptions to be made in the estimation of firm shock processes, the distinction between observed sales patterns and unobserved underlying firm profitability shock behavior underscores the importance of using a structural model to sort out the endemic endogeneity problem and recover consistent estimates of the importance of short-term shocks.

3.3 The Implications of Short-Term Shocks and Sensitivity

With estimated model parameters in hand, we can now explore the quantitative implications of short-term shocks and sensitivity for firm investment, value, and misallocation. For many of the following results, we compare the estimated model's behavior to that implied by a counterfactual benchmark model - the No Distortion Benchmark - which features an otherwise identical parameterization but no short-term investment frictions with $\tau_i = \tau_x = 0$.

In Figure 5 we first plot firm investment policies as a function of the short-term shock ν in the estimated and counterfactual models. In the estimated model, investment choices for firms slope up as a function of short-term shocks, i.e., firms facing negative short-term shocks today will cut the value of their long-term investment and R&D expenditures. Naturally, the benchmark model exhibits zero investment sensitivity to short-term shocks.

In Figure 6, we plot the distinct impulse responses of profitability, output, tangible investment, and R&D to one-standard deviation short-term and long-term shocks. By construction, the exogenous impulses in the top left have very different persistence properties, but as can be seen on the bottom row both forms of investment comove with both profitability shocks. Although the investment responses are short-lived for the short-term shocks, the change in capital stocks does generate a more than perfectly transitory change in firm output in the top right after a short-term shock.[8]

The top panel of Table 7 reports the share of variance of the tangible and intangible investment rates in the estimated model accounted for by the short-term shock. Almost 10% of the observed tangible investment fluctuations can be accounted for by short-term shocks and sensitivity, a meaningful departure from the benchmark of 0%. Finally, the bottom panel of Table 7 reports the average loss of fundamental firm value in the model with estimated short-term shock sensitivities relative to the model with zero sensitivity. The value loss, around 0.3% or $50-60 billion at current US market capitalizations, reflects meaningful misallocation of capital.

[8] An astute observer of the patterns in Figure 6 might also note that output exhibits a somewhat nonstandard hump-shaped response, and investment flows exhibit quite persistent respones, after a long-term shock. These dynamics are generated by the presence of multiple capital inputs with complementarity and adjustment costs, implying that it is optimal for firms to build up each capital stock in a self-reinforcing and hump-shaped process. In particular, the model does not rely on second-order or other exotic forms of adjustment costs to generate such behavior.

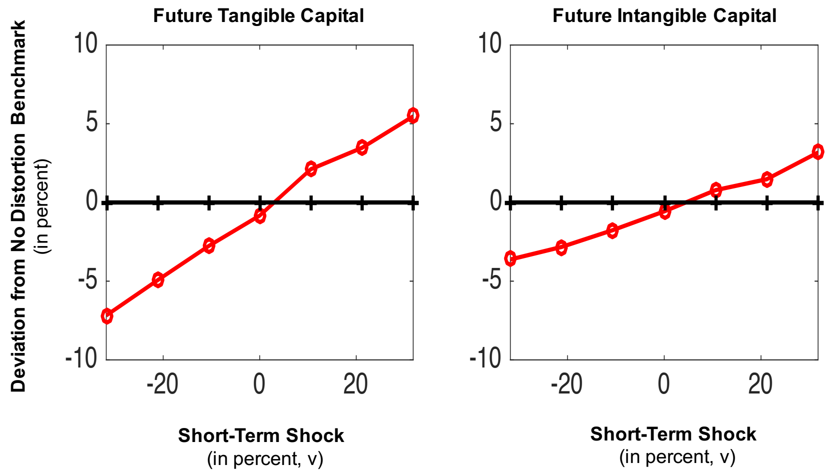

Figure 5: Distorted Model Features Investment Sensitivity

Note: The figure above plots capital choices k' (left panel) and o' (right panel) as a function of today's short-term shock ν. The figure plots the conditional mean of policies from the stationary distribution implied by the global solution of the best fit model (in red with circles, with distortions) and the no distortion benchmark (in black with plus signs). The no distortion policies are constant in ν and normalized to 0. Policies for the best fit model with distortions are expressed as percentage deviations from the no distortion case.

To summarize, our estimated model implies that a meaningful fraction of observed investment fluctuations stem from responses of forward-looking investment to purely transitory, short-term shocks and that the resulting misallocation of capital inputs at firms leads to a sizable average loss of firm value.

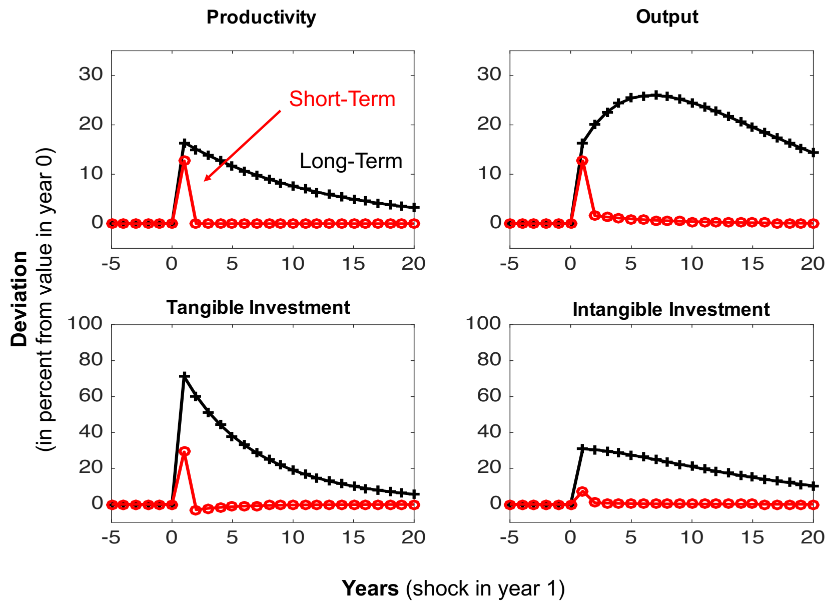

Figure 6: Impulse Response to Profitability Shocks

Note: The figure plots impulse responses in the best fit model to a one-standard deviation profitability shock to a firm which comes from short-term ν (in red with circles) and long-term η (in black with plus signs) sources. The shocks arrive in year 1. Each panel plots percentage deviations of the indicated variable from the pre-shock or steady-state value at the firm, with the top left panel representing the exogenous impulse and all other panels representing endogenous responses. The impulse response functions are computed from a linearized solution to the model and are therefore invariant to initial conditions or scaling.

Table 7: Implications of Short-Term Sensitivity

Variance Decomposition	% from ν
Tangible Inv. Rate $\frac{i}{k}$	8.7
Intangible Inv. Rate $\frac{x}{o}$	2.2

Destroyed Value	Amount
Average Loss	-0.3%
S&P 500	-$58b
Total U.S.	-$72b

Note: The top panel above reports the share of variance of the tangible and intangible investment rates accounted for by the ST shock ν in the linearized solution of the best fit model.The first row of the bottom panel of the table above reports the average change in firm value from the introduction of investment distortions in the best fit model, relative to a no distortion benchmark, computed using the stationary distribution of the distorted best fit model implied by the global solution of the model. The second (third) line converts the value loss to dollar magnitudes using the market capitalization of the S&P 500 (the total US stock market) in October 2016, equal to $19.3 trillion ($23.9 trillion) as reported by *Standard & Poors*.

4 Challenges for Researching Short-Term Shocks

Before concluding, we'd like to highlight and discuss several obvious challenges faced by any research in this area including our own work.

First, researchers rarely observe true underlying profitability shocks at firms, whether they be due to TFP, demand-side factors, or some combination of the two. So when exploring the data in the reduced-form such as in Table 2 or computing target moments for structural analysis as in the estimation in Section 3.2, researchers often must exploit the information contained in less than perfect proxies for firm profitability. On the one hand, firm-level TFP estimates often require the application of a range of stringent assumptions embedded in production function estimation procedures, and researchers often fail to observe all of the required series for such estimation in any case. On the other hand, rougher proxies such as firm sales are conceptually distinct from underlying shocks in that they embed both the exogenous impulses hitting firms as well as the endogenous responses of input and investment choices to those shocks. This endogeneity issue is not exclusive to sales, since in models with intangible capital even perfectly measured TFP will also embed the response of intangible investment to shocks, but the endogeneity issue is particularly severe for sales or other output measures. Our approach in this paper is a hybrid technique, exploiting the low number of assumptions and high sample size provided by the sales data but using the structure of a dynamic firm investment model to sort out the resulting endogeneity and hence underlying fundamental TFP shock behavior. While onerous in some dimensions, because it requires the specification of a structural model, we would argue that the burden is not too high given the standard nature of our model structure and offers a useful path forward for inference on the true underlying TFP process.

Second, we would also like to highlight a related but distinct measurement challenge in our analysis. In particular, although the Bayesian panel estimator of the process (1) possesses strong finite-sample properties for estimation of the process parameters ρ, σ_η^2, and σ_ν^2, quick Monte Carlo analysis reveals that the smoothed estimates $\{\hat{v}_{j,t}\}_{j,t}$ of the short-term shock process are in general quite noisy proxies for the true underlying short-term shock panel $\{\nu_{j,t}\}_{j,t}$. Therefore, we caution researchers seeking to exploit information on the short-term sensitivity of investment to rely fairly little on the individual smoothed estimates of shocks in a particular firm-fiscal year observation. By contrast, our approach of using the overall estimated sensitivities from the full sample in Table 2 avoids reliance on any single smoothed short-term shock estimate $\hat{\nu}_{j,t}$. As shown in our investigation of the identification of structural sensitivity parameters through the use of these reduced-form sensitivities in Figure 4, the full-sample estimates from our two-stage estimation procedure contain considerable information and allow for identification of the underlying investment sensitivities in the context of a broader structural estimation exercise.

Third, note that firm-level data such as our Compustat sample is inevitably contaminated by measurement error to some degree. A natural question is whether the prevalence of short-term shocks we estimate reflects the magnitude of fundamental transitory shocks or simply iid measurement error noise. In our case, the positive investment comovement or sensitivity we estimate - as well as the currently brief textual analysis of firm statements and news reports - gives us assurance that some meaningful fraction of the short-term shocks reflect fundamental variation at firms. We'd also like to highlight that even in an extreme - and empirically implausible - case in which all of the short-term shocks we estimate reflect measurement error, the same lessons about inference in firm investment models that we highlight in Section 2.1 go through without modification. In any case, a straightforward extension of our model framework and estimation exercise can incorporate the internal estimation of measurement error with the addition of a structural shock as well as extra information on firm fundamental behavior from, say, observed shifts in variable inputs such as materials.

5 Conclusion

We argue that firms face two distinct forms of profitability shocks: short-term, transitory changes and long-term, persistent shocks. Empirically, short-term shocks account for around 40% of the variance of the innovations to profitability in a given year, a large fraction. Long-term investment in both tangible and intangible inputs comoves and exhibits considerable sensitivity to short-term shocks, at odds with simple benchmark models of firm investment. We argue that the presence of short-term shocks plays a crucial role for inference in firm-level models of investment, cautioning researchers to avoid the use of misspecified models with a conventional univariate persistent shock process but also highlighting the role of estimated investment sensitivities to short-term shocks as a useful new target moment for researchers studying investment frictions in a wide set of models. Using a quantitative model of firm investment subject to general investment frictions inducing short-term shock sensitivity, we argue that investment is misallocated meaningful due to this sensitivity, generating sizable losses in firm value from capital misallocation.

We end by highlighting two natural extensions of our analysis which are the subject of ongoing work. Empirically, the addition of a range of informative covariates - for example, firm leverage - may allow for the estimation of heterogeneity in firm short-term shock sensitivities which would serve as additional useful target information for models of particular firm investment frictions. On the theoretical side, our estimates of sensitivity in intangible investment to short-term shocks suggest that a model of endogenous firm growth based on intangible investment - rather than the stationary model of intangible capital that we model above - may allow for richer and more quantitatively meaningful statements about the misallocation of intangible investment.

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Appendixes: Data and Model

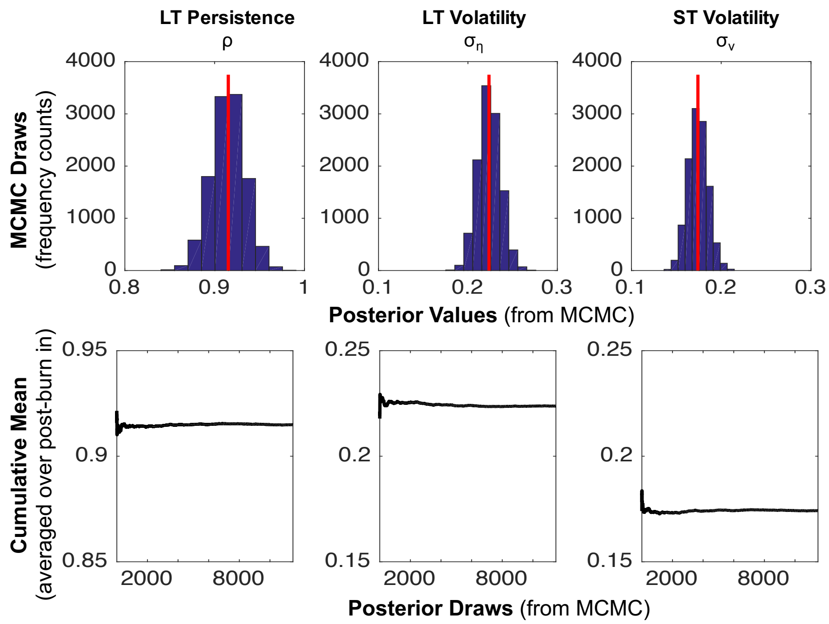
A Empirical Analysis

A.1 Bayesian Panel Estimation of Firm Shock Processes

We follow the procedure in Nakata and Tonetti (2015) for Bayesian estimation of the process in (1). The key insight is that a MCMC posterior sampler can be designed to draw from the joint posterior of $(\rho, \sigma_\eta^2, \sigma_\nu^2)$ given a panel - balanced or unbalanced - of data on $\{z_{j,t}\}_{j,t}$ for firms $j = 1, ..., N$ and $t = 1, ..., T$. Then, to construct the posterior draws, engage in an iterative conditional sampling or Gibbs sampling procedure with the following steps and assumptions:

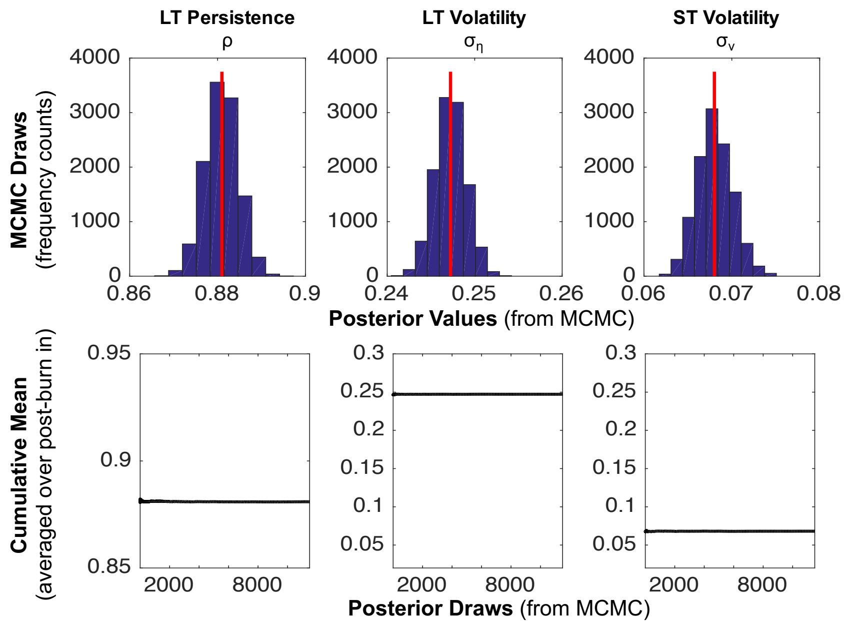
- *Conjugate Priors*
  Normal prior for ρ, inverse-Wishart for variances, choose uninformative parameters
- *MCMC or Gibbs Sampling*
  Draw iteratively from conditional posteriors for each component
- *Tractable Individual Blocks*
  Conditional posterior draws only require OLS estimation, variance calculations, application of Kalman filter and Carter-Kohn smoother given state-space structure

The outcomes of interest include posterior draws for 1) process parameters ρ, σ_η^2, and σ_ν^2 and 2) smoothed unobserved shocks $\{\varepsilon_{jt}, \nu_{jt}\}_{j,t}$. Figures A.1-A.2 display diagnostics for the estimation procedure underlying Table 2.



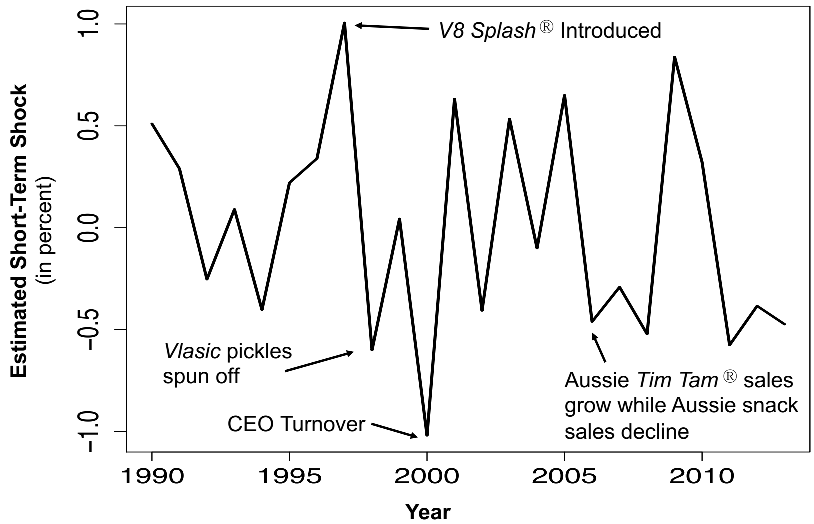
Note: The top row plots posterior marginal histograms for each profitability process parameter, together with posterior medians in red. The bottom row plots the cumulative mean for progressive MCMC draws of each parameter. The total MCMC process is implemented with 15,000 draws and a 3,500-draw burn-in period.

Figure A.1: Well Behaved MCMC Procedure for TFP Panel



Note: The top row plots posterior marginal histograms for each profitability process parameter, together with posterior medians in red. The bottom row plots the cumulative mean for progressive MCMC draws of each parameter. The total MCMC process is implemented with 15,000 draws and a 3,500-draw burn-in period.

Figure A.2: Well Behaved MCMC Procedure for Sales Panel

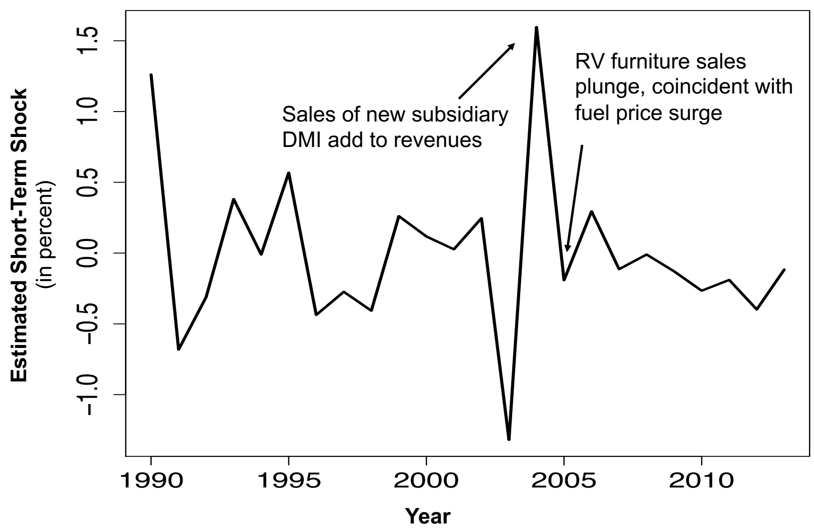


Note: The figure above plots the median posterior smoothed estimate of $\hat{\nu}_{jt}$ for the indicated company in each year of the sample period. The profitability proxy used for estimation is log sales, net of firm and year fixed effects. Events indicated on the plot reflect analysis of news reports on the company downloaded from the *Factiva* database as well as reported information from the company's annual reports.

Figure A.3: Campbell's Soup Corporation: A Food Manufacturer Subject to Taste Shocks

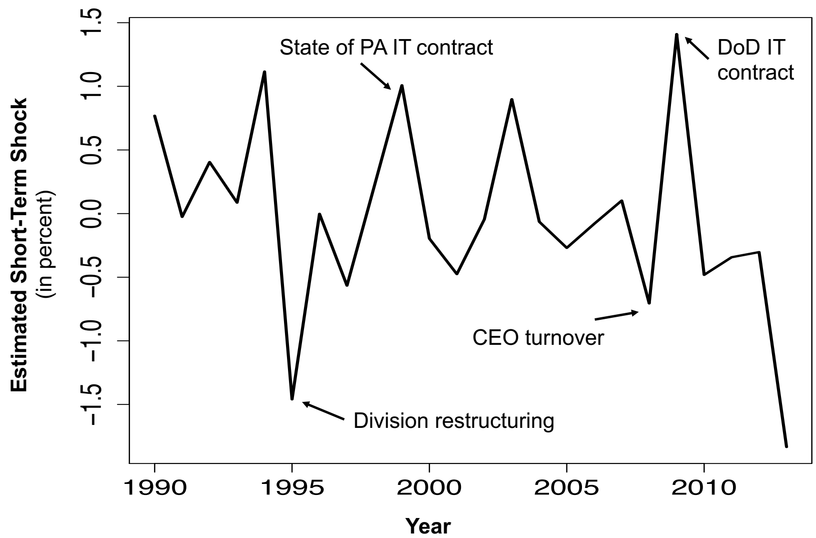
A.2 Anecdotal Analysis of Short-Term Shocks & News Reports

Figures A.3-A.5 display smoothed estimates of short-term shocks for selected companies together with anecdotal manual labelling of various event information gleaned from the firm's annual reports, public disclosures, and news coverage of the firms.



Note: The figure above plots the median posterior smoothed estimate of $\hat{\nu}_{jt}$ for the indicated company in each year of the sample period. The profitability proxy used for estimation is log sales, net of firm and year fixed effects. Events indicated on the plot reflect analysis of news reports on the company downloaded from the *Factiva* database as well as reported information from the company's annual reports.

Figure A.4: Flexsteel Industries: An RV Manufacturer Affected by Weather and Associated Energy Price Shocks



Note: The figure above plots the median posterior smoothed estimate of $\hat{\nu}_{jt}$ for the indicated company in each year of the sample period. The profitability proxy used for estimation is log sales, net of firm and year fixed effects. Events indicated on the plot reflect analysis of news reports on the company downloaded from the *Factiva* database as well as reported information from the company's annual reports.

Figure A.5: Unisys Corporation: A Mainframe Company subject to Reorganization Disruption

Table 1: A Comparison of AR(1) Estimates

Source	LT Persistence	LT Volatility	Sample
Nikolov & Whited (2014)	0.597	0.282	U.S. Public Firms
Hennessy & Whited (2007)	0.684	0.118	U.S. Public Firms
Gourio & Rudanko (2014)	0.88	0.23	U.S. Public Firms
Midrigan & Xu (2013)	0.25	0.5	Korean Manuf. Estab.
Winberry (2016)	0.78	0.32	U.S. Firms
Cooper and Ejarque (2003)	0.857	0.1	U.S. Manuf. Estab.
Clementi & Palazzo (2015)	0.55	0.22	U.S. Manuf. Estab.
Castro, et al. (2015)	≈ 0.45	≈ 0.25	U.S. Manuf. Estab.
Asker, et al. (2014)	≈ 0.85	≈ 0.75	U.S. Manuf. Estab.
Cooper & Haltiwanger (2006)	0.885	0.64	U.S. Manuf. Estab.
Khan & Thomas (2008)	0.859	0.15	U.S. Manuf. Estab.
Khan & Thomas (2013)	0.659	0.118	U.S. Manuf. Establ.
TFP Panel	0.92	0.22	U.S. Public Firms

Note: The table above summarizes estimates or parameterizations of univariate AR(1) TFP processes from the literature in macroeconomics and corporate finance on investment.

A.3 A Survey of Estimated AR(1) Processes

Table 1 reports the estimated persistence and volatility of shocks in firm-level models from a range of papers in the literature on firm investment in macroeconomics and corporate finance.

B Model Analysis

B.1 Baseline Model of Firm Investment

The baseline model of firm investment which we analyze in Section 3 is laid out here in recursive form for convenience:

$$V^M(\varepsilon,\nu,k,o)=\max_{i,x}\left\{\begin{array}{c} y-p_i i-p_x x \\ -AC_k(k,i)-AC_o(o,x) \\ -\nu\left(\tau_i\frac{i}{k}+\tau_x\frac{x}{o}\right)\end{array}+\frac{1}{1+r}\mathbb{E}V^M(\varepsilon',\nu',k',o')\right\}$$

$$\log z=\varepsilon+\nu,\quad \varepsilon=\rho\varepsilon_{-1}+\eta$$

$$\eta\sim N(0,\sigma_\eta^2),\quad \nu\sim N(0,\sigma_\nu^2)$$

$$y=zk^{\alpha_k}o^{\alpha_o},\quad \alpha_k+\alpha_o<1$$

$$k'=(1-\delta_k)k+i,\quad o'=(1-\delta_o)o+x$$

$$AC_k(k,i)=\phi_k\left(\frac{i}{k}\right)^2k,\quad AC_o(o,x)=\phi_o\left(\frac{x}{o}\right)^2o$$

$$V(\varepsilon,\nu,k,o)=\left\{\begin{array}{c} y^*-p_i i^*-p_x x^* \\ -AC_k(k,i^*)-AC_o(o,x^*)\end{array}+\frac{1}{1+r}\mathbb{E}V(\varepsilon',\nu',k',o')\right\}$$

In our main quantitative analysis and counterfactual calculations, we globally solve this model using discretization and policy function iteration. The driving processes are discretized following Tauchen (1986), and the endogenous states are assigned log-linear grids. In Fortran on a personal laptop with heavy parallelization, the solution of this model for a given set of parameters, as well as simulation of firm behavior, takes only a few seconds. However, even more speed gains can be achieved through exploiting the approximate log-linearity of this model of smooth investment behavior, so we employ a local first-order perturbation approach to the solution and simulation of the model as an input into our SMM procedure.

Note that the model used to compute the variation in investment volatility as a function of the share of transitory variance in Figure 2 is simply the model described directly above, with $\alpha_o=\tau_i=\tau_x=\phi_o=0$, i.e., a standard Q-theoretical model of investment with decreasing returns to scale obtains immediately.

B.2 Financial Frictions Model of Firm Investment

The model of financial frictions with a dividend smoothing motive that we used to simulate and estimate the investment sensitivity to short-term shocks in Figure 3 is given below. The parameter ϕ_π governs the magnitude of the dividend smoothing motive.

$$V(\varepsilon,\nu,k)=\max_{k'}\left\{\begin{array}{c} zk^{\alpha_k}-p_i i \\ -AC_k(k,i)-\phi_\pi\left(y-p_i i\right)^2\end{array}+\frac{1}{1+r}\mathbb{E}V(\varepsilon',\nu',k',o')\right\}$$

$$\log z=\varepsilon+\nu,\quad \varepsilon=\rho\varepsilon_{-1}+\eta$$

$$\eta\sim N(0,\sigma_\eta^2),\quad \nu\sim N(0,\sigma_\nu^2)$$

$$k' = (1 - \delta_k)k + i$$

$$AC_k(k, i) = \phi_k \left(\frac{i}{k} \right)^2 k$$