Firms' Marginal Propensities to Invest

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Abstract

Few heterogeneous-firm models are calibrated to firms' responses to income shocks because estimates of these responses are lacking. We estimate the average marginal propensity to invest (MPI) of firms in the US, that is, the share of a transitory sales shock that firms use for investment. In Compustat data, the dynamics of firms' sales are well described by a transitory-permanent process, so a semi-structural approach can identify the response of investment to transitory sales shocks. This response is statistically significant and the average MPI is 0.22. Younger firms, smaller firms, and non-dividend-paying firms exhibit significantly higher MPIs. Given that Compustat over-represents older and dividend-paying firms, our result is a lower bound on the response over the universe of firms. Our heterogeneity analyses make it possible to infer results for other sets of firms.

Keywords: Marginal Propensities to Invest; Firm Heterogeneity; Income Risk; Financial Constraints; Investment Dynamics.

JEL Classification: E22, E32, D25, D22

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1 Introduction

Investment plays a central role in business cycle dynamics. Despite contributing less to GDP than aggregate consumption, it is far more volatile: in the U.S., over the 1970–2025 period, the standard deviation of the growth rate of investment is more than four times that of real GDP growth (U.S. Bureau of Economic Analysis 2025a,b).

Yet, as Winberry et al. (2025) note, current frontier business cycle models account for aggregate consumption fluctuations more carefully than they account for aggregate investment fluctuations. Heterogeneous Agent New Keynesian (HANK) models feature rich household heterogeneity to match estimated consumption responses to short-lived income shocks, but they do not attempt to match firm investment responses to the same shocks.

Heterogeneous-firm models, pioneered by Hopenhayn (1992), are now being integrated into New Keynesian frameworks (Jeenas 2025; Ottonello and Winberry 2020; Winberry et al. 2025). These models provide important new insights into how firm heterogeneity shapes the aggregate transmission of shocks. So far, however, they have focused almost exclusively on responses to monetary policy, not to the response to a one-time change in cash flow or income. The latter is important because it has implications for the effectiveness of fiscal policies towards firms. It also has implications for the channels through which monetary policy operates: Winberry et al. (2025) suggest that, in the presence of high-MPI firms, there could be large indirect channels of monetary policy transmission to investment.

One reason why models are not yet calibrated to the firms' response to a one-time change in cash flow or income might be that the empirical literature lacks estimates of the marginal propensity to invest (MPI) out of direct, short-lived income shocks—in contrast to the extensive literature on the households' marginal propensity to consume (MPC) out of short-lived income shocks.

This paper addresses that gap. In a large sample of listed U.S. firms, we document transitory sales shocks that dissipate within four years, and we estimate the average response of investment to these shocks. We find that the response of investment is statistically significant and economically important: the average MPI out of the contemporaneous income change caused by a short-lived sales shock is 0.22, and the average MPI out of the total (net present value) income change caused by this shock is 0.11, with considerable heterogeneity across firms.

To identify these shocks and estimate their effect, we adapt the semi-structural approach developed in the consumption literature by Meghir and Pistaferri (2004) and Blundell, Pistaferri, and Preston (2008) (BPP hereafter). This method identifies the effects of transitory shocks separately from those of permanent shocks, which is crucial for calibrating business-cycle models. The key insight is that a transitory shock generates negative covariance with future income growth, but only over a finite number of periods. The covariance structure therefore identifies both the existence and the persistence horizon of transitory shocks. Future income growth can then be used as an instrument to isolate the effect of transitory shocks from that of permanent shocks. The BPP method is now widely used in macroeconomics (Berger, Guerrieri, and Lorenzoni 2018; Bilbiie et al. 2025; Ganong et al. 2025; Kaplan and Violante 2010) and has been shown to recover reliable estimates of household responses to shocks. Estimates based on the BPP method align with those obtained from natural experiments (Commault 2022).

One important adaptation that we make is to develop, on top of our baseline estimator, a verification estimator that detrends sales income from the level of production-factors. This avoids capturing the feedback loop by which firm investment improves subsequent capacity and thus affects subsequent sales. With the production factor controls, the sales increase caused by this feedback loop is not in our measure of detrended sales and the persistence of the shocks that we estimate is not contaminated by the investment response to the shock. That way, the shock and its persistence can be interpreted in the same way as households' income shocks and their persistence.

We apply this method to Compustat, a panel of publicly listed U.S. firms observed at annual frequency from 1970 to 2019. Compustat covers nearly the entire universe of U.S. listed firms and accounts for the vast majority of U.S. equity market capitalization. While it excludes small and privately held firms, it is widely accessible and well understood, so our results can be replicated without the access restrictions that typically apply to administrative data covering all firms in a country. We use the annual rather than the quarterly version because most administrative firm-level datasets are available only at annual frequency, so that our method carries over directly to those settings.

Using these data, we document that detrended firm sales, net of observable firm characteristics, show a covariance structure similar to that of household income: sales growth covaries negatively with future sales growth, but only over a few periods ahead. This pattern suggests that the sales process is well captured by a transitory-permanent decomposition. Transitory shocks to firms' sales are more persistent than transitory shocks to households' income, dissipating over four years rather than one. However, even within this longer horizon, roughly half of their total impact is contemporaneous. The persistence is the same when we detrend sales from the effect of the factors of production, thereby eliminating the impact of the feedback loop. Thus, this persistence is not primarily driven by the feedback loop of investment on sales.

Applying the BPP method, we estimate the elasticity of investment with respect to a transitory sales shock at 0.47, significant at the 1% level. Combining this elasticity with the average capital-to-sales ratio in our sample yields an MPI estimate of 0.22: on average, a $1 increase in contemporaneous sales caused by a transitory shock is associated with an increase in capital of 22 cents. Such a shock also raises future sales: in net present value, the expected future gain is $1.04, so the total increase in sales income is $2.04. This implies an average MPI out of the net present value of total sales of 0.11. Which of the two numbers is closer to the amount that a firm would invest out of a one-time income change depends on the firm's abilities to borrow against future sales income. For a constrained firm, whose constraints are not relaxed by the inflow of sales income, the MPI out of the contemporaneous sales increase coincides with how much it would invest out of a one-time income gain. For an unconstrained firm or for a firm whose constraints are relaxed when its contemporaneous sales increase, the MPI out of the total change in sales income is the best measure of how much it would invest out of a one-time income gain.

To the extent that investment raises the capital stock in a permanent or highly persistent way, its effect on future sales is absorbed by the permanent component. The transitory increase in sales that we measure is therefore not itself the outcome of past investment. In a robustness exercise, we re-estimate the MPI detrending log sales of the effect of current capital and employment. This removes the influence of factor accumulation, so the shocks we consider do not reflect past investment. This specification yields a slightly larger MPI, 0.28, significant at the 5% level.

We further show that MPIs vary systematically with firm characteristics. Younger firms, smaller firms (with lower total assets, number of employees or revenue), and non-dividend-paying firms have significantly higher MPIs than older, larger, and dividend-paying firms. Since firm age, size, and dividend status are standard proxies for financial constraints, these results suggest that constrained firms rely more heavily on changes in their income to fund investment. We also examine the differences by leverage and by liquidity-to-asset ratio, which are sometimes used as proxies for constraints as well. One limitation of these proxies is that their relation with financial constraints is theoretically ambiguous: firms that anticipate becoming constrained may, for instance, hold a larger liquidity buffer. The differences by leverage and liquidity-to-asset ratio are not significant. Comparing point estimates, less leveraged firms and firms with higher liquidity-to-asset ratios have higher MPIs than more leveraged firms and firms with lower liquidity-to-asset ratios. By sector, the MPI in mining is higher than in manufacturing and the tertiary sector. This heterogeneity matters both for the design of fiscal policy and for aggregate dynamics more broadly, since the effect of changes in aggregate demand on aggregate investment depends on the distribution of firms. In particular, because monetary policy operates partly through aggregate demand, the way firms respond to income shocks can help explain the heterogeneous response to monetary policy shocks documented in the literature.

This heterogeneity also speaks to the interpretation of our estimate. Because the transitory shocks we identify decay slowly, they raise the expected marginal return to capital, and a firm with no financial friction could invest for that reason alone. Our estimates would then measure the response of investment to a change in expected profitability rather than to a change in resources. Two features of the results are hard to reconcile with that reading. Firms that standard proxies identify as unconstrained face the same change in expected returns and show no detectable response, though they are the firms best placed to act on it. And across sectors the response is stronger where the shock is shorter lived: firms in the tertiary sector face transitory shocks that dissipate over three years rather than four and have a higher pass-through, the opposite of the ordering the expected-return channel predicts.

Finally, because Compustat over-represents older, larger, and dividend-paying firms, which we find have lower MPIs, our estimated average MPI is likely below the average over the full universe of U.S. firms. Equipped with our estimates, we can impute the average MPI even from a cross-sectional or short dataset in which firm characteristics are known. We apply this imputation strategy to the Business Dynamics Statistics, which reports the share of the universe of U.S. firms that fall in different characteristics bins. Our imputation implies an average MPI of 0.27, and an average MPI out of the net present value of the shock of 0.17, for U.S. firms with at least five employees in the four sectors we estimate, which account for 84 percent of firms above that threshold in 2023.

Related Literature

Empirical effect of changes in cash flow. We are not the first to measure firms' responses to changes affecting their income or cash flow. There are two main strands of empirical literature that have looked at the relationship between investment and income. The first one examines the sensitivity of investment to internal cash flows with linear regressions. It builds on the influential contribution of Fazzari, Hubbard, and Petersen (1988), and now constitutes an extensive literature, including Hubbard (1998), Kaplan and Zingales (1997), Gomes (2001), and Almeida, Campello, and Weisbach (2004).[1] This literature documents strong and positive correlations between cash flow and investment. More recently, Alati et al. (2024) consider the correlation between investment and sales forecast errors coming from deviations of realized sales from expected sales. They also find large responses of investment to these surprises. However, a central challenge in this literature is that changes in cash flow might reflect long-run changes in productivity or demand. These long-run changes would also raise the future expected marginal product of capital, and thus raise investment. As a result, the observed increase in investment may not reflect the immediate effect of the short-run increase in cash flow but that of the long-run changes in the marginal product of capital. While the literature controls for Tobin's Q to address this, the

[1] See Mulier, Schoors, and Merlevede (2016) for a comprehensive review.

problem persists as existing proxies for Tobin's Q are only imperfect measures of the marginal product of capital. The contribution of our paper is to disentangle the permanent and transitory shocks, and to provide estimates of the investment responses to transitory shocks only.

The second strand of the literature relies on natural experiments to identify the effect of exogenous shocks on investment. These papers have looked at different types of shocks. Early in this literature, a first subgroup exploited shocks to firms' internal funds. Blanchard, Lopez-de-Silanes, and Shleifer (1994) study eleven firms that received cash windfalls from won or settled lawsuits, choosing cases in which the windfall leaves the firm's investment opportunities unchanged. They find that only a small fraction of the windfall is spent on increasing investment. Lamont (1997) uses the 1986 collapse in oil prices, which reduced oil companies' cash flow. He shows that the non-oil divisions of the firms affected by the oil shock significantly cut their investment. In this paper, we aim to capture a similar parameter, the response to an increase in cash flow, in a larger and less selected sample of firms and shocks.

A second subgroup exploits tax reforms, which change revenue but also the net cost of investing. Cummins, Hassett, and Hubbard (1994) use a set of changes in the U.S. corporate tax code over 1962-1988. They examine the effect of the price of capital on investment, and consider mostly permanent changes in this price. They find that investment responds strongly to the price of capital. Goolsbee (1998) considers, over the same period of time, the specific impact of the investment tax credits. He measures its impact on both the price of capital and investment. He finds that much of the investment tax credit is absorbed by a rise in the price of capital goods. Because these reforms alter the net cost of investing, the responses they identify reflect a substitution effect rather than a pure change in firms' resources. Our shocks leave the net cost of investment unchanged.

A third subgroup of natural experiment papers examines policies that change the timing of inflows and outflows of firms' liquidity. This can be either policies making tax deductions available earlier (House and Shapiro 2008; Zwick and Mahon 2017), or policies inducing firms to set aside larger amounts for pension contributions (the 1994 pension reform increased the funding thresholds required for the firms' pension plans) and thus reducing liquidity (Rauh 2006). The three papers find large effects of liquidity on investment: the bonus depreciation raised investment while the change in pension contribution reduced investment. These changes in the timing of liquidity inflows and outflows can be decomposed into two components: a small change in revenue that depends on the idiosyncratic interest rate faced by a firm and on the amount it deducts, and a large decrease in liquidity constraints. From this, it is difficult to estimate MPIs. Our contribution is to measure the response to an increase in revenue only.

A last subgroup of papers looks at the effect of a firm receiving more contracts, often because of a public spending shock in some places but not in others (Bellifemine, Couturier, and Tozzo 2025; Coviello et al. 2022; Hebous and Zimmermann 2021). They find that receiving a government contract raises the firm's revenue significantly, with an investment response that ranges from weak (Hebous and Zimmermann 2021) to very large (Bellifemine, Couturier, and Tozzo 2025). These shocks are relatively persistent: in Bellifemine, Couturier, and Tozzo (2025), the contemporaneous effect of the public spending shock on revenue is as large as its effect two years after the shock. In that paper, firms are also overoptimistic about the shock's impact, so that winning a public procurement contract raises revenue expectations above the already high and persistent increase in revenues that actually realizes. Our contribution is to measure the response to shocks of shorter duration, and to consider idiosyncratic shocks that do not come with a local increase in public spending.

Modeling of firms' income. We also build on and contribute to the more recent literature on the estimation of the firm income process, which moves away from modeling firm income shocks as Gaussian AR(1) innovations.

Our paper builds on a literature that identifies idiosyncratic shocks to firms by detrending firm-level sales income from the effect of a set of observable firm characteristics, and then decomposing the residual into a permanent and a transitory component. Guiso, Pistaferri, and Schivardi (2005) provide the framework. They distinguish between transitory and permanent shocks to firm performance after detrending from the effect of firm-level controls. Fagereng, Guiso, and Pistaferri (2018), Juhn et al. (2018), Melcangi and Sarpietro (2026) and Fella et al. (2022) adopt the same transitory-permanent representation of firms' sales. Galaasen et al. (2025)

use a narrative-based approach to confirm that the shocks after this detrending are indeed idiosyncratic. In line with these papers, we adopt a transitory-permanent specification.

Regarding the distribution of the shocks, Bloom et al. (2018) document the importance of uncertainty shocks. Berlingieri et al. (2025) and Melcangi and Sarpietro (2026) establish that the log-change in firms' income is more leptokurtic and fat-tailed than implied by an AR(1) process with Gaussian shocks. In line with these findings, we let the shocks be drawn from unspecified distributions that can be mixtures of Gaussians, accommodating uncertainty shocks and a more fat-tailed and leptokurtic distribution. Our additional contribution is to estimate the skewness and kurtosis of the distribution of transitory shocks specifically, rather than those of the overall sales change, which conflates transitory and permanent shocks. We document that transitory shocks are not significantly skewed but are leptokurtic and fat-tailed, as the overall revenue change is.[2]

HANK models. In macroeconomics, the importance of micro-level estimates of the response of consumption to short-lived income shocks has been emphasized in a number of HANK models (Auclert 2019; Auclert, Rognlie, and Straub 2025; Kaplan, Moll, and Violante 2018; McKay, Nakamura, and Steinsson 2016). The recent paper of Winberry et al. (2025) stresses the importance of matching the response of investment to short-lived income shocks as well. We contribute to this literature by providing estimates that can be used for calibration.

[2]Melcangi and Sarpietro (2026) and Fella et al. (2022) suggest that the lower persistence in the tails of the distribution can be driven by a varying persistence of the permanent shocks, so the past has a lesser effect after a large shock. Since we focus on the response to transitory shocks, which are not affected by this change in persistence, we abstract from it. We do let the permanent shock be an AR(1) with persistence below one, since Arellano et al. (2024), who develop this model for the persistence of household income shocks, suggest that the lower persistence in the tails also implies that the permanent component is an AR(1) with persistence below one rather than a random walk.

2 Modeling Sales and Investment

2.1 Sales

Based on the literature on modeling firm income, pioneered by Guiso, Pistaferri, and Schivardi (2005), and on the covariance structure of log-sales growth that we report in Section 5.2, we assume that the log of firm-level income, denoted $\ln(\tilde{y}_{i,t})$, follows a transitory-permanent process:

$$\ln(\tilde{y}_{i,t}) = p_{i,t} + \mu_{i,t} + \gamma' z_{i,t} + \xi^y_{i,t}, \tag{1}$$

$$\text{with } p_{i,t} = p_{i,t-1} + \eta_{i,t}, \tag{2}$$

$$\mu_{i,t} = \varepsilon_{i,t} + \sum_{s=1}^{k} \theta_s \, \varepsilon_{i,t-s}. \tag{3}$$

The permanent component $p_{i,t}$ is a random walk with innovation $\eta_{i,t}$. These innovations capture permanent changes that are not driven by changes in demographics or production factors, such as shifts in demand, in market share, or in technology. The transitory component $\mu_{i,t}$ follows an $MA(k)$ process with innovation $\varepsilon_{i,t}$. These innovations reflect short-lived shocks such as machine breakdowns, temporary tax rebates, or administrative closures. The term $z_{i,t}$ denotes a vector of observable firm demographics and the firm's levels of the production factors, capital and employment, and γ their effect on log-income. The term $\xi^y_{i,t}$ denotes measurement error.

The shocks ε, η and ξ^y are serially uncorrelated and mutually independent.

After removing the effect of observable firm characteristics $\gamma' z_{i,t}$, detrended log-income, denoted without the tilde as $\ln(y_{i,t})$, is

$$\ln(y_{i,t}) \equiv \ln(\tilde{y}_{i,t}) - \gamma' z_{i,t} = p_{i,t} + \mu_{i,t} + \xi^y_{i,t}. \tag{4}$$

Taking first differences, detrended log-income growth is

$$\Delta \ln(y_{i,t}) = \eta_{i,t} + \varepsilon_{i,t} + \sum_{l=1}^{k} (\theta_l - \theta_{l-1}) \varepsilon_{i,t-l} - \theta_k \varepsilon_{i,t-1-k} + \Delta \xi^y_{i,t}, \tag{5}$$

with $\theta_0 = 1$. Thus, log-income growth at t contains the permanent innovation at t, the transitory innovation at t, the past transitory innovations up to $t-1-k$ (because the transitory component mean-reverts), and the change in measurement error.

This model makes the detrended component of sales an exogenous process. But firms may still affect their own sales through their input choices. Our verification estimator addresses this by including the level of capital and employment in the set of characteristics we control for, so that our measure of sales variation is the component that is not driven by the firm's own input decisions.

2.2 Investment

We allow firms' log-capital stock $\ln(\tilde{k}_{i,t})$ to depend flexibly on the history of shocks, as follows

$$\ln(\tilde{k}_{i,t}) = f(\eta_{i,t}, \ldots, \eta_{i,1}, \varepsilon_{i,t}, \ldots, \varepsilon_{i,1}, \xi^k_{i,t}, \ldots, \xi^k_{i,1}) + \delta' z_{i,t}, \tag{6}$$

where ξ^k_{it} captures measurement error or idiosyncratic capital shifters, and δ the effects of observable firm characteristics $z_{i,t}$. We do not impose functional form restrictions on $f(\cdot)$. This specification encompasses most standard models of firm dynamics.

The shocks ξ^k are drawn independently over time, independently of the income shocks, and independently of observable firm characteristics.

After removing observable firm characteristics $\delta' z_{i,t}$, detrended log-capital, denoted without the tilde as $\ln(k_{i,t})$, is

$$\ln(k_{i,t}) \equiv \ln(\tilde{k}_{i,t}) - \delta' z_{i,t} = f(\eta_{i,t}, \ldots, \eta_{i,1}, \varepsilon_{i,t}, \ldots, \varepsilon_{i,1}, \xi^k_{i,t}, \ldots, \xi^k_{i,1}). \tag{7}$$

3 Estimating Sales-Shock Parameters and Investment Responses

3.1 Sales-Shock Parameters

Besides our main result, the estimation of the MPI, we provide estimates of the characteristics of the income process. We estimate two sets of parameters: (i) the MA coefficients of the transitory income process, θ_s with $1 \leq s \leq k$; and (ii) the third and fourth central moments of the transitory shocks, $E[\varepsilon^3]$ and $E[\varepsilon^4]$, which govern their skewness and kurtosis.

The persistence parameters matter for interpreting how large the contemporaneous impact of a transitory shock is relative to its impact in later periods. They are identified from the covariances between $\Delta \ln(y_{t+k+1})$ and $\Delta \ln(y_t), \ldots, \Delta \ln(y_{t+k})$, as described in Appendix A.

The skewness and kurtosis of the transitory shocks matter for understanding how much these shocks depart from a normal distribution, so that papers calibrating the response of investment to transitory shocks can use the correct underlying shock distribution. We obtain them from higher-order moments that depend on $E[\varepsilon^3]$ and $E[\varepsilon^4]$. The skewness is identified from the covariance between $\Delta \ln(y_{t+k+1})$ and $(\Delta \ln(y_t))^2$, and the kurtosis from the covariance between $\Delta \ln(y_{t+k+1})$ and $(\Delta \ln(y_t))^3$. The expressions for these covariances are in Appendix A.

3.2 Pass-Through Coefficient

Our empirical strategy builds on the semi-structural approach developed by Blundell, Pistaferri, and Preston (2008) to estimate households' marginal propensities to consume out of transitory income shocks.

The transitory and permanent innovations $\varepsilon_{i,t}$ and $\eta_{i,t}$ are unobserved. Thus, regressing capital growth on current income growth would capture the effect of both transitory and permanent innovations on the chosen level of capital. This is the standard critique of cash-flow regressions: they confound the effects of long-term changes in sales prospects with the effects of short-run changes in income.

The key insight of this approach is that future income growth identifies the mean reversion associated with transitory shocks while being orthogonal to contemporaneous permanent innovations. This makes it possible to identify the effect of transitory shocks without directly observing these underlying shocks.

The pass-through coefficient of a transitory sales shock to capital growth is

$$\phi^{\varepsilon} \equiv \frac{\mathrm{Cov}(\Delta \ln k_{i,t},\ \varepsilon_{i,t})}{\mathrm{Var}(\varepsilon_{i,t})}, \tag{8}$$

the average elasticity of capital growth to the shock. Because past log-capital $\ln k_{i,t-1}$ is orthogonal to the transitory shock $\varepsilon_{i,t}$, this coincides with the pass-through to the capital level

$$\phi^{\varepsilon} = \frac{\mathrm{Cov}(\ln k_{i,t},\ \varepsilon_{i,t})}{\mathrm{Var}(\varepsilon_{i,t})}. \tag{9}$$

We use the light notation ϕ^{ε} throughout because growth and level coincide contemporaneously; the two diverge only at future horizons, where we distinguish them explicitly (Appendix C.4).

This coefficient equals the average elasticity of capital to a transitory shock,

$$\phi^{\varepsilon} = \mathbb{E}\left[\frac{\partial \ln k_{i,t}}{\partial \varepsilon_{it}}\right], \tag{10}$$

under either of two conditions. First, if log-capital growth is linear in the current transitory shock, which is the counterpart for investment of the linearity assumption BPP make for consumption. Second, if log-capital growth is quadratic in the shock and either the skewness $E[\varepsilon_{i,t}^3]$ is not statistically distinguishable from zero, as we show in Table 3, or the shocks are drawn from a normal distribution or a mixture of normals (Commault 2022).

To identify the effect of transitory shocks separately from that of permanent shocks, we exploit the fact that future income growth reflects the mean reversion of transitory shocks but not of permanent shocks, which by definition do not revert. Specifically, the covariance between log-income growth at t and at $t+k+1$ captures the variance of the transitory shock, multiplied by minus the persistence parameter θ_k:

$$\text{Cov}(\Delta \ln y_{i,t}, \Delta \ln y_{i,t+k+1}) = -\theta_k \, \text{Var}(\varepsilon_{i,t}). \tag{11}$$

The covariance between log-capital growth at t and log-income growth at $t + k + 1$ captures the covariance between log-capital growth and the transitory shock multiplied by $-\theta_k$:

$$\text{Cov}(\Delta \ln k_{i,t}, \Delta \ln y_{i,t+k+1}) = -\theta_k \, \text{Cov}(\Delta \ln k_{i,t}, \varepsilon_{i,t}). \tag{12}$$

Taking the ratio with the corresponding income autocovariance identifies the pass-through coefficient

$$\widehat{\phi}^{\varepsilon} = \frac{\text{Cov}(\Delta \ln k_{i,t}, -\Delta \ln y_{i,t+k+1})}{\text{Cov}(\Delta \ln y_{i,t}, -\Delta \ln y_{i,t+k+1})} = \frac{\text{Cov}(\Delta \ln k_{i,t}, \varepsilon_{i,t})}{\text{Var}(\varepsilon_{i,t})} = \phi^{\varepsilon}. \tag{13}$$

Note that the covariance between log-capital growth at t and log-income growth at earlier periods, between $t + 1$ and $t + k$, would also capture the effect of $\varepsilon_{i,t}$ on $\ln k_{i,t}$. These are included in the original BPP estimator. Here, we follow the approach of Commault (2022) and exclude them because log-income growth at earlier periods also depends on transitory shocks before t. By not using them, we do not have to assume that these transitory shocks before t have no effect on log-capital growth at t.

3.3 Marginal Propensity to Invest (MPI)

Bounding the MPI out of the current income change. The MPI out of the current sales income change caused by a transitory shock, which we call the MPI, is defined for firm i at time t as

$$MPI^{\varepsilon}_{i,t} = \frac{\partial \tilde{k}_{i,t} / \partial \varepsilon_{it}}{\partial \tilde{y}_{i,t} / \partial \varepsilon_{i,t}} = \frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}} \cdot \frac{\partial \ln k_{i,t}}{\partial \varepsilon_{i,t}} = \frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}} \cdot \frac{\partial \Delta \ln k_{i,t}}{\partial \varepsilon_{i,t}}. \tag{14}$$

Since $\tilde{k}_{i,t}$ is a stock, $\Delta \tilde{k}_{i,t}$ is net investment. Depreciation at t depends on capital at $t - 1$ and is therefore unaffected by $\varepsilon_{i,t}$, so the contemporaneous response of the capital stock coincides with the response of gross capital expenditure.

The average MPI over all firms and periods in a sample is then

$$MPI^{\varepsilon} = \mathbb{E}[MPI^{\varepsilon}_{it}] = \mathbb{E}\left[\frac{\tilde{k}_{i,t}}{\tilde{y}_{it}} \cdot \frac{\partial \Delta \ln k_{i,t}}{\partial \varepsilon_{it}}\right]. \tag{15}$$

While $\phi^{\varepsilon} = \mathbb{E}\left[\frac{\partial \Delta \ln k_{i,t}}{\partial \varepsilon_{it}}\right]$, which we estimate, captures the average elasticity, the average MPI depends on the joint distribution of the elasticities $\frac{\partial \Delta \ln k_{i,t}}{\partial \varepsilon_{i,t}}$ and of the capital-to-income ratios $\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}$ in the population. However, we can estimate lower and upper bounds on the average MPI.

First, we find suggestive evidence that $\mathrm{Cov}(\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}, \frac{\partial \Delta \ln k_{i,t}}{\partial \varepsilon_{i,t}})$ is zero or positive in our data: the firms that have a capital-to-income ratio above the median also have a higher pass-through (0.59 vs 0.36), although the difference is not statistically significant (see Appendix Table A3). This means that either the true MPI^{ε} (if the covariance is zero) or a lower bound $\underline{MPI}^{\varepsilon}$ on the MPI^{ε} (if the covariance is positive) is

$$\begin{aligned} MPI^{\varepsilon} &= \mathbb{E}\left[\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\right] \underbrace{\mathbb{E}\left[\frac{\partial \Delta \ln k_{i,t}}{\partial \varepsilon_{it}}\right]}_{\approx \frac{\mathrm{Cov}(\Delta \ln k_{i,t}, \varepsilon_{i,t})}{\mathrm{Var}(\varepsilon_{i,t})}} + \underbrace{\mathrm{Cov}(\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}, \frac{\partial \Delta \ln k_{i,t}}{\partial \varepsilon_{i,t}})}_{\geq 0} \\ &\geq \mathbb{E}\left[\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\right] \frac{\mathrm{Cov}(\Delta \ln k_{i,t},\, \varepsilon_{i,t})}{\mathrm{Var}(\varepsilon_{i,t})} = \mathbb{E}\left[\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\right] \hat{\phi}^{\varepsilon} \equiv \underline{MPI}^{\varepsilon}. \end{aligned} \tag{16}$$

Second, we have that $\frac{\partial\left(\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}} \Delta \ln k_{i,t}\right)}{\partial \varepsilon_{i,t}} = \frac{\partial \frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}}{\partial \varepsilon_{i,t}} \Delta \ln k_{i,t} + \frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}} \frac{\partial \Delta \ln k_{i,t}}{\partial \varepsilon_{i,t}}$. We also find that $\mathrm{Cov}(\frac{\partial \frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}}{\partial \varepsilon_{i,t}}, \Delta \ln k_{i,t})$ is positive in our data. This means that an upper bound $\overline{MPI}^{\varepsilon}$ on the MPI is

$$\mathbb{E}\left[\frac{\partial\left(\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\Delta\ln k_{i,t}\right)}{\partial\varepsilon_{i,t}}\right] = \mathbb{E}\left[\frac{\partial\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}}{\partial\varepsilon_{i,t}}\Delta\ln k_{i,t}\right] + \mathbb{E}\left[\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\frac{\partial\Delta\ln k_{i,t}}{\partial\varepsilon_{i,t}}\right]$$

$$\underbrace{\mathbb{E}\left[\frac{\partial\left(\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\Delta\ln k_{i,t}\right)}{\partial\varepsilon_{i,t}}\right]}_{\approx\frac{\mathrm{Cov}\left(\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\Delta\ln k_{i,t},\varepsilon_{i,t}\right)}{\mathrm{Var}(\varepsilon_{i,t})}} = \mathbb{E}\left[\frac{\partial\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}}{\partial\varepsilon_{i,t}}\right]\underbrace{\mathbb{E}[\Delta\ln k_{i,t}]}_{=0} + \underbrace{\mathrm{Cov}\left(\frac{\partial\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}}{\partial\varepsilon_{i,t}},\Delta\ln k_{i,t}\right)}_{\geq 0} + \underbrace{\mathbb{E}\left[\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\frac{\partial\Delta\ln k_{i,t}}{\partial\varepsilon_{i,t}}\right]}_{MPI^{\varepsilon}}$$

$$\overline{MPI}^{\varepsilon} \equiv \frac{\mathrm{Cov}\left(\frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}}\Delta\ln k_{i,t},\ \varepsilon_{i,t}\right)}{\mathrm{Var}(\varepsilon_{i,t})} \geq MPI^{\varepsilon} \tag{17}$$

To be conservative in our results, and because the difference in pass-through by capital-to-sales ratio is positive but not significant, which suggests that the lower bound is the closer of the two, our main measure of the MPI is the first one

$$MPI^{\varepsilon} \approx \underline{MPI}^{\varepsilon}.$$

In Section 6.2, we compute the upper bound, to verify that it is not too far from our lower bound so that the latter is a meaningful indicator of the true MPI.

MPI out of the net present value of the shock. Although our shock is not permanent, it affects sales for more than one period, so we also compute the MPI out of the net present value of the transitory income shock. The MPI out of the net present value of the transitory income shock is

$$\begin{aligned} MPI_{it}^{NPV^{\varepsilon}} &= \frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t} + \sum_{s=1}^{k}\theta_s E_{t,i}[\tilde{y}_{i,t+s}](1+r)^{-s}} \cdot \frac{\partial\ln k_{i,t}}{\partial\varepsilon_{it}} &(18)\\ &\approx \frac{\tilde{k}_{i,t}}{\tilde{y}_{i,t}(1+\sum_{s=1}^{k}\theta_s(1+r)^{-s})} \cdot \frac{\partial\ln k_{i,t}}{\partial\varepsilon_{it}} &(19)\\ &\approx \frac{MPI_{i,t}^{\varepsilon}}{(1+\sum_{s=1}^{k}\theta_s(1+r)^{-s})}. &(20)\end{aligned}$$

The approximation holds if the idiosyncratic shocks at t are similar to the expected future values of the same shocks over the next k periods, so that $E_{t,i}[\tilde{y}_{i,t+s}] \approx \tilde{y}_{i,t}$

for $s \leq k$. Under this approximation, the net present value of the shocks is $(1 + \sum_{s=1}^{k} \theta_s (1+r)^{-s})$ and the net present value MPI is the MPI divided by it.

4 Data

4.1 Data Sources and Sample Construction

We implement our estimator using firm-level data from the *Compustat Annual* database, a panel of publicly listed U.S. firms. Because the database is widely used in the empirical corporate finance and macroeconomics literatures, results based on it are easy to verify or replicate. Its long time dimension is valuable because the transitory shocks we study are relatively persistent, so identifying them requires observing firms over many periods. Its rich balance-sheet information lets us detrend our variables of interest using a broad set of firm characteristics and conduct heterogeneity analyses. Its main limitation is that it excludes private firms and so covers only publicly listed companies, which are typically larger. Our sample spans 1970 to 2019; we stop in 2019 to avoid the large shocks associated with the COVID-19 pandemic.

Our sample construction follows standard practice in the literature and stays close to Ottonello and Winberry (2020). A detailed description of the sample selection is in Appendix B.

4.2 Variables Description

Our main variables of interest are firm sales and capital. Sales, which correspond to our $\tilde{y}_{i,t}$, are commonly used as a measure of a firm's resources, since transitory sales fluctuations translate into transitory cash-flow fluctuations (see, e.g., Bloom et al. (2018) and Melcangi and Sarpietro (2026)). While value added would be a natural theoretical counterpart, its Compustat approximation as sales minus the cost of goods sold introduces heterogeneity across firms and industries in what the constructed series measures, making sales the cleaner empirical proxy. We therefore use Compustat value added only in our robustness exercise.

Firm capital, which corresponds to our $\tilde{k}_{i,t}$, is the book value of the tangible capital stock of firm i at the end of year t, constructed using a perpetual inventory method.

For controls and heterogeneity analyses, we use other firm variables, following standard practice in the literature. The age of a firm is the number of years since the earliest of the following: the firm's first appearance in Compustat, its year of incorporation from WorldScope, and its first appearance in the Center for Research in Security Prices (CRSP). Firm size is the log of lagged total assets. Dividend status is a zero-one dummy variable indicating whether the firm paid dividends. Leverage is total debt divided by the book value of total assets. Liquidity is the ratio of cash and short-term investments to the book value of total assets. Firms are classified into broad sectors using the SIC Division structure, defined by ranges of two-digit SIC codes.[3] Tobin's Q is the ratio of the market value of assets to their book value. We also use the location of the firm, defined as the state in which the firm's headquarters are located. Table 1 reports summary statistics on the main variables used in the analysis. The sample exhibits substantial heterogeneity in firm size, age, and investment behavior.

Table 1: Descriptive Statistics

Variable	Mean	SD	p25	p50	p75
Log capital	3.63	2.49	1.88	3.57	5.33
Log sales	5.00	2.31	3.45	5.04	6.59
Log capital growth	0.02	0.26	−0.09	−0.01	0.10
Log sales growth	0.04	0.29	−0.07	0.04	0.14
Age	22	24	7	14	27
Log total assets	4.95	2.23	3.40	4.88	6.46
Log employment	−0.23	2.14	−1.78	−0.21	1.31
Leverage	0.29	0.37	0.06	0.22	0.39
Tobin's Q	1.97	1.95	1.02	1.36	2.11

Notes: Capital, sales, and total assets are reported as log millions of dollars; employment is the log number of employees (in thousands), so the median of −0.21 corresponds to roughly 810 employees. The sample consists of 206,952 firm-year observations covering 20,830 unique firms over 1970–2019.

[3] We consider the sectors agriculture, forestry, and fishing; mining; construction; manufacturing; transportation and communications; wholesale trade; retail trade; and services.

5 Implementing the Estimation

5.1 Detrending from Observable Characteristics

We construct detrended log-sales and log-capital, as defined in equations (4) and (7), by removing the linear effect of observable characteristics $z_{i,t}$ on log-sales and log-capital. To do so, we regress log-sales and log-capital on the following set of observable characteristics: year dummies, age-category dummies[4], industry dummies, dummies for the U.S. state in which the firm is headquartered, and the first and second lags of total assets (size), leverage and Tobin's Q. Apart from firm size, none of these controls are essential to our results, and we present their effects one by one in Appendix C.5, Table A6.

The first differences of the residuals from these regressions are our measures of sales and capital growth, $\Delta \ln(y_{i,t})$ and $\Delta \ln(k_{i,t})$.

5.2 Estimating Moments

We first describe the moments of the income and investment dynamics on which our identification strategy is built.

Table 2: Covariances of Log-Sales Growth and Log-Capital Growth

	$\Delta y_{i,t}$	$\Delta y_{i,t+1}$	$\Delta y_{i,t+2}$	$\Delta y_{i,t+3}$	$\Delta y_{i,t+4}$	$\Delta y_{i,t+5}$	$\Delta y_{i,t+6}$
$\text{Cov}(\Delta y_{i,t}, \cdot)$	0.0879***	−0.0157***	−0.0043***	−0.0026***	−0.0016***	−0.0028***	0.0002
	(0.0017)	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$\text{Cov}(\Delta k_{i,t}, \cdot)$	0.0438***	−0.0115***	−0.0023***	−0.0014***	−0.0004	−0.0014***	0.0001
	(0.0009)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Observations	81,637	67,539	56,280	47,164	39,977	35,929	32,512

Notes: We report results from the estimate of the covariance of the row variable with the column variable, where $\Delta y_{i,t}$ and $\Delta k_{i,t}$ are the growth rates of log sales and log capital, detrended of the controls listed in Section 5. Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The top panel in Table 2 reports autocovariances of detrended log-sales growth at different horizons. It shows that detrended log-sales growth exhibits strong negative autocovariance at future horizons. This is consistent with the presence of a transitory

[4] We also present in Appendix C.5, Table A7 results with age and age squared.

component in firm-level sales. The autocovariances are statistically significant up to five periods ahead. Their magnitude declines sharply after the first lag and remains small thereafter, consistent with mean reversion. While later autocovariances are smaller, the large sample size allows them to be estimated precisely.[5] Because the covariance of log-sales growth with future log-sales growth is statistically significant up to $t + 5$, and becomes much smaller and insignificant afterwards, we adopt an $MA(4)$ specification for the transitory income process in the baseline analysis. This means that $\theta_s \neq 0$ for $s \leq 4$, and $\theta_s = 0$ for $s > 4$.

The bottom panel of Table 2 reports covariances between detrended log-capital growth and detrended log-sales growth at different horizons. It shows that the covariance between log-capital growth, our measure of investment, and contemporaneous sales growth is positive and strongly significant: firms with higher sales growth also exhibit higher capital growth. The covariances between log-capital growth and future log-sales growth are negative at horizons $t + 1$ through $t + 5$. The covariance at $t + 5$ is significant and negative, at -0.0014. This is consistent with capital responding positively to the transitory component of income that subsequently reverses: the only component of log-sales growth at $t + 5$ that can affect log-capital growth at t is the transitory income shock at t; it lowers log-sales growth at $t + 5$ but raises log-capital growth at t so the covariance between the two is negative.

These cross-covariance patterns provide direct empirical support for the identifying variation exploited by the estimator.

5.3 Implementation Method

We estimate the parameters by GMM. This means that we select the value that minimizes the distance between the empirical counterparts to our theoretical moments: for the pass-through coefficient ϕ^ε, we select the value that minimizes the distance between $E[\Delta \ln k_{i,t}\, \Delta \ln y_{i,t+5}]$ and $\phi^\varepsilon\, E[\Delta \ln y_{i,t}\, \Delta \ln y_{i,t+5}]$, where $\Delta \ln y_{i,l}$ and $\Delta \ln k_{i,l}$ denote detrended log-income and log-capital growth at horizon l. We apply the same minimum-distance logic to all the identifying moments derived in Section 5.2.

[5] The declining observation counts across horizons reflect the unbalanced panel structure. Appendix Table A2 verifies that results are robust to restricting the sample to firms observed at all horizons simultaneously.

In the baseline, we estimate jointly the pass-through coefficient, the MPI, the MPI NPV, the persistence parameters θ, and the variance, skewness, and kurtosis of the transitory shocks. Our standard errors are clustered at the firm level.

6 Results

6.1 Sales Shocks Parameters Estimates

Before turning to our main results, we provide estimates of the characteristics of the sales process. We estimate two sets of parameters: (i) the MA coefficients θ, which measure how the transitory shocks fade out over time; and (ii) the variance, skewness, and kurtosis of the transitory shocks. The identifying moments are described in Appendix A.

Table 3: Variance and Persistence of Transitory Shocks Across Specifications

	Baseline	Production-Factors Controls	AR(1) $\rho = 0.95$
θ_1	0.51^{***}	0.46^{***}	0.47^{***}
	(0.02)	(0.03)	(0.03)
θ_2	0.32^{***}	0.27^{***}	0.30^{***}
	(0.02)	(0.03)	(0.03)
θ_3	0.17^{***}	0.15^{***}	0.16^{***}
	(0.02)	(0.03)	(0.03)
θ_4	0.08^{***}	0.07^{***}	0.07^{***}
	(0.02)	(0.02)	(0.02)
var(ε)	0.035^{***}	0.020^{***}	0.026^{***}
	(0.002)	(0.001)	(0.002)
skew(ε)	-0.89	-3.55	0.14
	(1.31)	(3.21)	(1.86)
kur(ε)	28.75^{***}	19.67	44.38^{***}
	(9.80)	(24.65)	(16.29)
Observations	33,453	32,003	33,453

Notes: Column (1) reports the baseline GMM estimates described in section 5.3. Column (2) augments the detrending of log sales with controls for log capital and log employment. Column (3) replaces the random-walk assumption on the permanent component with an AR(1) process with persistence parameter $\rho = 0.95$. $\text{var}(\varepsilon) = E[\varepsilon^2]$ is the variance, $\text{skew}(\varepsilon) = E[\varepsilon^3]/(E[\varepsilon^2])^{3/2}$ the Pearson moment coefficient of skewness, and $\text{kur}(\varepsilon) = E[\varepsilon^4]/(E[\varepsilon^2])^2 - 3$ the excess kurtosis. Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Baseline. The first panel of the first column in Table 3 reports the estimates of the MA coefficients θ of the transitory sales process.[6] All four coefficients are positive, statistically significant, and monotonically decreasing with lag order. They imply that a transitory shock that raises current sales by 10% raises sales one year later by 5.1%,

[6] The sample used for estimation is smaller than the one described in Table 1. Identification requires observing a firm's sales growth from t to $t + 5$, together with capital growth and lags of the firm-level controls.

two years later by 3.2%, three years later by 1.7%, and four years later by 0.8%. As discussed in Section 3.3, these estimates imply that a transitory shock raising current sales by one dollar raises expected future sales by 51 cents one year later, 32 cents two years later, and so on. This means that the impact of a transitory sales shock is halved after one year and divided by three after two years: it diminishes substantially over time. This interpretation requires that the model holds, so there is no feedback loop of investment on the part of sales we measure, and that current shocks are not too extreme, so that detrended expected future sales stay close to current sales.

These estimates also make it possible to compute the net present value at t of a transitory shock that raises current sales by \$1. For $r = 0.02$[7], it is

$$NPV^{\varepsilon} = 1 + \sum_{s=1}^{k} \frac{\theta_s}{(1+r)^s} = 2.04. \tag{21}$$

The expected increase in future sales amounts to an additional \$1.04 in net present value. Thus, roughly half of the net present value impact of a transitory shock is contemporaneous, and the other half comes from expected future sales.

The second panel of the first column presents the estimates of the variance, skewness, and kurtosis of the transitory shocks. The estimated variance of the transitory sales shock is 0.035. The magnitude of a one-standard-deviation shock is therefore $\sqrt{0.035} = 0.187$: a one-standard-deviation transitory shock raises contemporaneous sales by 18.7 log points. The Pearson moment coefficient of skewness is -0.89 but is not statistically different from zero, so we cannot reject symmetry. The Pearson excess kurtosis is large, positive, and significantly different from zero, although the standard error is large, so the distribution is strongly leptokurtic. The distribution of the transitory shocks thus exhibits the same features as the distribution of overall log-sales changes (Berlingieri et al. 2025; Melcangi and Sarpietro 2026).

[7] Because the transitory shock dissipates within four years, the net present value is not very sensitive to the discount rate: at $r = 0.10$, closer to firms' perceived cost of capital, it falls to 1.91 and the implied $MPI^{NPV^{\varepsilon}}$ rises only from 0.11 to 0.12.

Production-factor controls. An important difference from the consumption literature is that, while consumption is unlikely to affect future income, investment increases the capital stock and thereby can affect future firm sales. To check the magnitude of this effect, we design a verification estimator in which we additionally control for log capital and log employment in the detrending of log sales. This removes from our measure of sales income the component of future sales driven by factor accumulation, in particular investment. The second column of Table 3 shows that the point estimates of the MA coefficients become a little smaller: a shock that raises sales by 10% at t raises sales by 4.6% (instead of 5.1%) at $t+1$, 2.7% (instead of 3.2%) at $t+2$ and so on. The θ_4 coefficient is still statistically significant, so the process is still an MA(4). The resulting NPV is $1 + \sum_{s=1}^{k} \frac{\theta_s}{(1+r)^s} = 1.92$ for $r = 0.02$ (and $1 + \sum_{s=1}^{k} \frac{\theta_s}{(1+r)^s} = 1.80$ for $r = 0.10$). Thus, the persistence remains close to that measured in the baseline: the fact that investment raises future sales drives a small part of, but not most of, the persistence that we measure. The variance of the shocks net of production factor variations is smaller, at 0.020 instead of 0.035. The skewness and kurtosis keep the same sign but have large standard errors.

AR(1) permanent component. The third column of Table 3 relaxes the random-walk assumption on the permanent component, allowing instead for an AR(1) structure with ρ the AR coefficient

$$p_{it} = \rho p_{i,t-1} + \eta_{it}. \tag{22}$$

Although the autocovariance structure reveals no long-run negative covariance with future log-income growth, as an AR(1) specification would imply, the effect might be small enough that it is not precisely measured. That is why we consider the effect of AR coefficients close but not exactly equal to one. Following Kaplan and Violante (2010), with an AR(1) specification, one recovers a correct estimator by using the quasi-difference $\ln y_{it} - \rho \ln y_{i,t-1}$ in place of the difference $\Delta \ln y_{it}$. One needs to make an assumption about the value of ρ. In Table 3 we show the results for $\rho = 0.95$. The MA coefficients and the variance of the transitory shocks become a little smaller as well. The point estimates of the skewness and kurtosis increase but have large standard errors.

6.2 Pass-Through and MPI Estimates

Table 4: Pass-Through and MPI: Main and Robustness Estimates

	Baseline	Production Factors Controls	AR(1) $\rho = 0.95$
Pass-through ϕ^{ε}	0.47***	0.62**	0.59***
	(0.15)	(0.29)	(0.21)
MPI^{ε}	0.22***	0.28**	0.27***
	(0.07)	(0.13)	(0.10)
$MPI^{NPV^{\varepsilon}}$	0.11***	0.15**	0.14***
	(0.03)	(0.07)	(0.05)
Observations	33,453	32,003	33,453

Notes: Column (1) reports the baseline GMM estimates described in section 5.3. Column (2) augments the detrending of log sales with controls for log capital and log employment. Column (3) replaces the random-walk assumption on the permanent component with an AR(1) process with persistence parameter $\rho = 0.95$. Standard errors in parentheses, clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Baseline. Table 4 reports our main pass-through and MPI estimates alongside three robustness checks.

Column (1) reports our main results, obtained with a GMM specification that estimates jointly the pass-through of sales to investment and the parameters of the sales process. The pass-through coefficient is 0.47, significant at the 1% level: a transitory income shock that raises current real sales by 10% raises the capital stock by 4.7%. Since the average capital-to-sales ratio is 0.46 in our estimation sample, this implies a lower bound on the MPI of 0.22: firms invest at least 22 cents of every dollar increase in sales generated by a contemporaneous transitory shock. Because a transitory shock also raises expected future sales, we also compute the MPI with respect to the net present value of the shock. We estimate that a $1 increase in sales generated by a contemporaneous transitory shock also leads to an additional $1.04 in future sales in present value, giving a total $2.04 net present value sales increase, the

MA coefficients we use to estimate the net present value increase in future sales are those we report in Table 3. The MPI out of the net present value of the sales increase is $0.22/2.04 = 0.11$.

Upper bound on the MPI. We use the lower bound on the MPI as our main result to remain conservative. To verify that our lower bound is not too far from the true MPI, we also compute the upper bound on the MPI, $\overline{MPI}^{\varepsilon}$, described in equation (17) in Section 3.3. We obtain a value of 0.32. The average of the lower and upper bound is 0.27, significant at the 5% level. The bounds are therefore relatively narrow, and the conservative choice is not too far from the average.

MPI vs MPI out of net present value. Which of the two MPI measures is relevant depends on the firm's access to finance. Both share the same numerator, the investment response $\partial \ln k / \partial \varepsilon$, and differ only in the denominator: the MPI divides by the contemporaneous inflow (\$1), while the $MPI^{NPV^{\varepsilon}}$ divides by the present value of the full sales stream (\$2.04). A liquidity-constrained firm cannot borrow against future sales, so only the current \$1 enters its budget set and the MPI is the relevant object. An unconstrained firm, for which only present-value wealth matters, would instead respond to a one-time increase in income by something closer to the $MPI^{NPV^{\varepsilon}}$.

Production-Factor Controls. We also implement a verification estimator, which controls for the feedback of investment on subsequent sales. Column (2) presents the results. Because the estimated variance of the shock is smaller (Table 3), while the covariance between log-investment growth and future log-sales growth is similar, the pass-through is larger than in the baseline. The MPI estimates are also slightly larger than in the baseline: we measure that $MPI^{\varepsilon} = 0.28$ and $MPI^{NPV} = 0.15$. However, the standard errors are somewhat larger. Our baseline estimate is thus again a conservative measure of the MPI.

AR(1) permanent component. Next, we relax the random-walk assumption on the permanent component, allowing instead for an AR(1) structure with $\rho = 0.95$ the AR coefficient. Column (3) presents the results. The pass-through, MPI and

$MPI^{NPV^{\varepsilon}}$ become slightly larger. We also try several values of $\rho \in [0.92, 0.99]$. We report the results for these specifications in Appendix C.3. In all cases, the response of investment increases as ρ decreases, so our baseline MPI estimate is conservative.

Comparison with the Literature. Our estimate of an MPI of 0.22 implies that firms invest, on average, at least an additional 22 cents per dollar of increase in sales income caused by a short-lived income shock. Table 5 presents existing estimates of investment responses to shocks. Apart from the earlier and more descriptive studies that rely on small samples of firms (Panel A), these papers identify the responses to changes in the cost of investing (Panel B), responses to timing shifts (Panel C) or long-term shocks (Panel D).

Table 5: Comparison of Firms' Investment Responses Across the Natural-Experiment Literature

Paper	Shock	What is identified	Estimate
This paper	Short-lived sales income shock	MPI	22 cents per \$ of sales; 0.47% capital growth per % of sales growth
Panel A. Short-lived income shocks			
Blanchard, Lopez-de-Silanes, and Shleifer (1994)	Legal windfall	Investment out of an unanticipated cash inflow	6 cents per \$ of windfall cash
Lamont (1997)	1986 oil price collapse	Within-firm reallocation of oil cash flow to non-oil segments	12–13 cents per \$ of oil cash flow
Panel B. Tax reforms changing the net cost of investing			
Cummins, Hassett, and Hubbard (1994)	U.S. corporate tax code changes, 1962–1988	Effect of the cost of capital on investment rate	-0.65-unit investment-to-capital ratio per 1 pp cost-of-capital measure
Goolsbee (1998)	Investment tax credits (ITC), 1962–1988	Impact of ITC on the price of capital	0.35-0.70 % price of capital per pp of ITC
Panel C. Reforms changing the timing of liquidity inflows/outflows			
House and Shapiro (2008)	Earlier tax deductions	Investment response to accelerated liquidity inflow	6-14 % price of capital per pp of earlier tax deduction
Zwick and Mahon (2017)	Earlier tax deductions	Eligible investment relative to ineligible	2.89% eligible investment per pp earlier tax deduction
Rauh (2006)	Larger pension contribution	Investment response to an anticipated cash outflow	-60–70 cents per \$ of required contribution
Panel D. Persistent or permanent demand shocks			
Hebous and Zimmermann (2021)	Federal procurement	Investment out of contracted revenue	10–15 cents per \$ of federal contracts
Coviello et al. (2022)	Municipality spending	Investment out of a permanent negative demand change	39–52 cents per \$ of municipal spending
Bellifemine et al. (2025)	Public procurement	Investment out of contracted revenue	0.85% capital growth per % revenue growth

iMPIs. We estimate the effect of a transitory sales shock on future investment and capital. At future horizons the effect on capital growth and on the capital level no longer coincide, so we distinguish them. Let

$$\phi^{\varepsilon,\,Fs\,\Delta k} \equiv \frac{\mathrm{Cov}(\Delta \ln k_{i,t+s},\, \varepsilon_{i,t})}{\mathrm{Var}(\varepsilon_{i,t})}, \qquad \phi^{\varepsilon,\,Fs\,k} \equiv \frac{\mathrm{Cov}(\ln k_{i,t+s},\, \varepsilon_{i,t})}{\mathrm{Var}(\varepsilon_{i,t})}, \tag{23}$$

denote the pass-through of a transitory sales shock at t to log-capital growth and to the log-capital level at horizon $t+s$. The baseline pass-through is the contemporaneous case, $\phi^{\varepsilon} = \phi^{\varepsilon,\,F0\,\Delta k} = \phi^{\varepsilon,\,F0\,k}$. The two measures coincide at $s = 0$ because the shock ε_t is orthogonal to past variables. Each coincides with the corresponding average elasticity, $\mathbb{E}[\partial \Delta \ln k_{i,t+s}/\partial \varepsilon_{i,t}]$ and $\mathbb{E}[\partial \ln k_{i,t+s}/\partial \varepsilon_{i,t}]$, under the same assumptions as in the contemporaneous case. The effect on capital growth is the most natural measure of investment taking place over the following years; the effect on the capital level captures the cumulative response of capital over the following years. We obtain a lower bound on the iMPIs in the same way we obtain a lower bound on the MPI from the pass-through. We describe the identifying moments in Appendix A.2.

We report the results in Table A5, Appendix C.4. None of the pass-through coefficients to future log-capital growth are statistically significant. The point estimates suggest a short-lived crowding-out of future investment by the investment made at the moment of the shock, and a larger crowding-in of investment three years after the shock. For the cumulative effect, the impact response is by construction our baseline result. Then, over the next two years, the cumulative effect is not statistically significant and smaller than the effect on impact. After three years, the elasticity of the capital stock is 0.55, significant at the 5% level. The corresponding iMPI is 0.25. Finally, the elasticity of capital after four years is 1.50, significant at the 5% level. The corresponding iMPI is 0.69. This suggests that, upon receiving \$1 at t, and a total of \$2.04 between t and $t+4$ in NPV at t (\$2.21 in NPV at $t+4$), capital is higher by 69 cents at $t+4$. The effect of sales income on capital is thus persistent.

7 Heterogeneity

We examine heterogeneity across groups of firms. How much investment responds to a transitory sales shock varies across firms, and this variation matters for policy design. Corporate fiscal policy typically targets specific types of firms, while monetary policy and household fiscal transfers affect aggregate demand, and hence firms' cash flows, unevenly across the firm distribution. In both cases, the aggregate investment response depends on how the MPI covaries with the firms a policy reaches.

7.1 Heterogeneity and Financial Constraints

An important dimension of heterogeneity is financial constraints. Financially constrained firms may have higher MPIs through two complementary channels. First, because these firms cannot raise more external finance, an additional dollar of sales adds directly to the funds available for investment. Second, earnings-based borrowing constraints, in particular interest coverage covenants, are widespread in corporate debt contracts (Drechsel 2023; Greenwald 2019; Lian and Ma 2021), so a transitory sales shock also relaxes borrowing capacity and allows investment to rise by more than the shock itself.[8]

Financial constraints are not directly observed in standard firm-level datasets, so we rely on widely used proxies. In standard firm dynamics models (e.g., Cooley and Quadrini 2001; Khan and Thomas 2008), firms are born with limited assets and cash flows and grow progressively until they exit their constraints. Along this path, firms invest as much as possible to reach their optimal scale and do not pay dividends. Firm age, size, and dividend payment status are therefore standard proxies for distance to a binding constraint. Leverage and liquidity have also been used as proxies for financial constraints, with the caveat that their mapping to constraint tightness is theoretically ambiguous in both cases.[9] Low leverage may indicate distance from a binding constraint or, conversely, denied credit. Low liquidity may indicate a firm close to a cash-flow constraint, or one that simply has no need to self-insure.

We estimate pass-through and MPIs within groups by running the same baseline estimator over our sample, but letting the pass-through coefficients and MPI^{ε} vary across groups. The parameters of the sales process (σ_{ε}^2 and θ_1–θ_4) are held common and estimated jointly. This way, differences in ϕ^{ε} reflect differences in the capital response per unit of an identically-defined shock. Equality tests are Wald tests on the group-specific ϕ^{ε} from the joint pooled estimation[10].

[8] Lian and Ma (2021) document that 80% of the value of U.S. nonfinancial firm debt is earnings-based.
[9] See Cloyne et al. (2023) for a thorough discussion of this issue.
[10] Median (and tercile) cutoffs are computed on the estimation sample, i.e. firm-years with non-missing income growth, capital growth, and the fifth lead of income growth, rather than on the full sample of

Table 6: Pass-Through and MPI Across Firm Characteristics

	Age		Size		Dividend Status	
	Young	Old	Small	Big	No Div.	Div.
Pass-through ϕ^{ε}	0.79***	0.13	0.79***	0.16	0.95***	0.13
	(0.25)	(0.18)	(0.27)	(0.15)	(0.32)	(0.14)
MPI^{ε}	0.38***	0.06	0.30***	0.09	0.43***	0.06
	(0.12)	(0.08)	(0.10)	(0.08)	(0.14)	(0.07)
Observations	33,453		33,453		33,425	
	Leverage		Liquidity		Employment	
	Low	High	Low	High	Small	Big
Pass-through ϕ^{ε}	0.65***	0.30	0.21	0.74***	0.94***	−0.02
	(0.24)	(0.21)	(0.16)	(0.27)	(0.31)	(0.12)
MPI^{ε}	0.23***	0.17	0.11	0.29***	0.47***	−0.01
	(0.09)	(0.12)	(0.08)	(0.11)	(0.16)	(0.05)
Observations	33,453		33,451		32,877	

Notes: Standard errors in parentheses, clustered at the firm level. Splits at the median: age (cutoff: 24 years); size (lagged log real assets, cutoff: 5.30, ≈\$200M); dividend status (lagged); leverage (lagged, cutoff: 0.20); liquidity (lagged, cutoff: 0.07); employment (lagged log employment, cutoff: 0.39). p-values from Wald tests on ϕ^{ε} *Age*: Young = Old: 0.040. *Size*: Small = Big: 0.059. *Dividend status*: No Div. = Div.: 0.022. *Leverage*: Low = High: 0.317. *Liquidity*: Low = High: 0.102. *Employment*: Small = Big: 0.005. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 reports pass-through coefficients and MPIs across six firm characteristics. The top panel reports results by firm age, size, and dividend status; the bottom panel reports leverage, liquidity and number of employees. All splits are at the median. Appendix Tables A9 and A10 confirm that the results hold when each characteristic is split into terciles.

Firm Age. The first column in the top panel of Table 6 shows that young firms exhibit a pass-through of 0.79 (significant at the 1% level), corresponding to an MPI of

Table 1. Because identification requires observing firms over several consecutive years, the estimation sample skews toward older and larger firms, so these cutoffs lie above their full-sample counterparts.

0.38. The estimate for older firms is much smaller (0.13) and statistically insignificant. The difference between the two groups is significant at the 5% level, and economically large. This is consistent with younger firms being more responsive to sales shocks. They face tighter financial constraints, having not yet established a credit history, accumulated pledgeable assets, or generated cash flow sufficient to fund their optimal level of investment.

Firm Size. The second column in the top panel of Table 6 presents the investment response estimates by size, that is, by total assets. Small firms exhibit a pass-through of 0.79 (significant at the 1% level), corresponding to an MPI of 0.30. The estimate for larger firms is much smaller (0.16) and statistically insignificant. The difference between the two groups is significant at the 10% level ($p = 0.06$). This pattern is consistent with the results by age and suggests as well that more constrained firms are significantly more responsive. Appendix Table A11 shows that the effect is driven by firms that are both young and small. The third column in the bottom panel of Table 6 shows that we obtain the same pattern using the number of employees as the size proxy.[11]

Dividend Status. In most firm dynamics models, firms do not pay dividends before growing out of their financial constraints. Dividend status has been used as a proxy for financial constraints since the early contribution of Fazzari, Hubbard, and Petersen (1988). The third column in the top panel of Table 6 shows that non-payers exhibit a precisely estimated pass-through of 0.95 and an MPI of 0.43, while dividend payers have a small and imprecise pass-through of 0.13 and an MPI of 0.06. The difference is significant at the 5% level. This is in line with constrained firms being the responsive ones and driving the aggregate response of investment to sales shocks. Appendix Table A11 shows that the effect is driven by young firms that do not pay dividends.

Alternative Proxies for Financial Constraints. We consider two characteristics that have occasionally been used as proxies for financial constraints: leverage, that is, total

[11]We also obtain the same pattern using the log of lagged real sales as the size proxy, as in Melcangi and Sarpietro (2026); see Appendix Table A9.

debt over the book value of total assets, and liquidity, that is, cash and short-term investments over the book value of total assets. Low-leverage firms exhibit a pass-through of 0.65 (significant at the 1% level) and an MPI of 0.23, while high-leverage firms exhibit a smaller and insignificant pass-through of 0.30. One interpretation is that low leverage reflects denied access to external credit, forcing firms to fund investment from internal cash flows and raising the sensitivity of investment to income shocks. However, the difference is not statistically significant (p = 0.317), suggesting that leverage is a noisier proxy for financial frictions in our sample than age, size, or dividend status. High-liquidity firms exhibit a pass-through of 0.74 (significant at the 1% level), while the estimate for low-liquidity firms is 0.21 and statistically insignificant. The difference is not significant at conventional levels (p = 0.102). The direction of the effects is consistent with the precautionary view of Bates, Kahle, and Stulz (2009): firms accumulate cash precisely because they anticipate that external finance will be costly or unavailable when needed, and these liquid asset holdings then enable them to act on shocks.

Holding the sales process common across the two groups being compared is an identifying restriction that buys precision: estimating the process separately within each group doubles the number of shock parameters and halves the sample identifying each of them, so the standard errors on the group-specific pass-throughs roughly double, and those on the difference between them more than double. But the estimated variance of the transitory shock is larger among the firms we classify as constrained. Since a group's pass-through is identified from a moment proportional to $\theta_k \operatorname{Var}(\varepsilon)$, imposing the common value raises the estimated pass-through of the more volatile group.

Appendix Table A12 reports estimates in which the variance, the persistence, and the order of the moving-average process are all estimated separately within each group. For our primary constraint proxies, age, size, employment, sales, and dividend status, the qualitative ordering of the point estimates is preserved, with the constrained group continuing to exhibit the stronger response. As expected, estimating separate processes within smaller subsamples substantially reduces statistical power. Consequently, the differences between groups are no longer estimated precisely enough to reject equality at conventional levels. We read this as indicating that the core pattern in Table 6 is not an artifact of the common-process assumption, while the assumption is what allows the difference between groups to be estimated with useful precision.

Comparison with the Monetary Policy Literature. The empirical literature on the response of investment to monetary policy consistently documents stronger responses among financially constrained firms. Cloyne et al. (2023) show that young firms and non-dividend payers are most sensitive. Durante, Ferrando, and Vermeulen (2022) and Bahaj et al. (2022) document stronger (employment) responses among young firms. Jeenas (2025) finds that firms with higher liquid asset holdings respond more strongly. Melcangi and Sarpietro (2026) show that young and small firms, and firms with higher liquidity holdings, are more sensitive to interest rate changes. Ottonello and Winberry (2020) show that low-leverage firms are the most responsive to monetary policy, with financial frictions steepening the marginal cost of investment finance for highly leveraged firms.

Our findings complement this literature. We document that young firms, non-dividend-payers, high-liquidity firms, and (more tentatively) low-leverage firms have higher MPIs. Because monetary policy operates in part through changes in aggregate demand, and hence through changes in firms' sales, the demographic and financial heterogeneity in MPIs that we document may account for part of the heterogeneous responses to monetary shocks documented in this literature.

7.2 Heterogeneity across Sectors

Firms in different sectors may respond differently to changes in their income because of differences in capital intensity, in the scalability of the production technology, or in financial structure. They may also face different sales processes. We allow for both, estimating the sales process and the pass-through separately within each group. We consider four sectors: mining; manufacturing; the tertiary sector, which pools wholesale trade, retail trade and services; and transportation and communications. Agriculture and construction are omitted because too few firms in these sectors are observed over the consecutive years the estimator requires.

The transitory sales process differs across sectors. Appendix Table A13 reports the sales process estimated sector by sector. Two patterns stand out. First, the order of the moving-average process is not the same everywhere: transitory shocks dissipate over four years in mining and manufacturing, three years in the tertiary sector, and a single year in transportation and communications. Second, both the persistence and the variance of the shock decline in the same order. The first-year coefficient θ_1 falls from 0.61 in mining to 0.50 in manufacturing, 0.36 in the tertiary sector and 0.34 in transportation, while the variance of the shock falls from 0.063 to 0.037, 0.022 and 0.013, against 0.035 in the pooled sample. The net present value of a one-dollar transitory shock therefore ranges from \$2.32 in mining to \$1.34 in transportation.

Table 7: Pass-Through and MPI by Sector

	Mining	Manufacturing	Tertiary	Transport
Shock process	$MA(4)$	$MA(4)$	$MA(3)$	$MA(1)$
NPV^{ε}	2.32	2.01	1.66	1.34
Pass-through ϕ^{ε}	0.47***	0.50**	0.71**	0.66**
	(0.16)	(0.22)	(0.36)	(0.28)
MPI^{ε}	0.89***	0.15**	0.25**	0.66**
	(0.32)	(0.07)	(0.13)	(0.27)
Observations	1,833	19,860	10,879	3,519
Firms	227	2,603	1,626	441

Notes: Standard errors in parentheses, clustered at the firm level. Estimates are obtained by running the GMM specification separately on each sector subsample, so the variance and persistence of the transitory shock, and the order of the moving-average process, vary across sectors; the underlying estimates are reported in Appendix Table A13. NPV^{ε} is the net present value of a transitory shock raising current sales by one dollar. The tertiary sector pools wholesale trade, retail trade and services; transportation and communications follows the SIC division structure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Pass-through and MPI by sector. Table 7 reports the results. The pass-through lies between 0.47 and 0.71 in all four sectors and is significantly different from zero in each. The MPI, by contrast, ranges from 0.15 in manufacturing to 0.89 in mining. Sectors differ much more in how much capital a given proportional response represents than in the proportional response itself. A mining firm and a manufacturing firm raise their capital stock by a similar percentage in response to a transitory sales shock of a given size; because mining holds six times as much capital per dollar of sales, the same elasticity translates into six times as many cents of investment. The one comparison of elasticities that is worth drawing is between the tertiary sector and manufacturing. Tertiary firms face shorter-lived shocks, dissipating over three years rather than four, and yet their pass-through is higher, 0.71 against 0.50. A firm facing no adjustment costs would do the opposite, responding more to the shock whose discounted stream of marginal products is larger. One interpretation is that capital in services is short-lived, divisible and comparatively easy to reverse, so that a temporary increase in demand is more readily accommodated by adding capital than it is in manufacturing, where capacity is lumpy and largely irreversible.

Interpreting the Response. The transitory shocks we identify persist for a few periods, so they raise the expected marginal return to capital, and a firm facing no financial friction could invest in response to them. Our pass-through could then reflect a change in expected profitability rather than a change in available resources. The heterogeneity in Table 6 speaks to this. A transitory shock of a given size shifts the expected path of proportional sales identically for a young firm and an old one. While this does not strictly guarantee identical changes in expected marginal returns, it restricts the scope for a pure expected-profitability explanation. If investment responded primarily through that channel, the response should be stronger among unconstrained firms, which can act on a change in expected profitability without having to fund it out of current cash flow. We find the opposite.

The point estimates across sectors in Table 7 offer suggestive evidence along similar lines. A frictionless expected-return channel might predict a larger response where the shock is more persistent, as a longer-lived shock increases the discounted stream of future marginal products. We do not observe this ordering in the point estimates. Transitory shocks dissipate over four years in manufacturing and three in the tertiary sector, yet the estimated pass-through is 0.50 in manufacturing against 0.71 in the tertiary sector. The lack of a strong positive relationship between persistence and pass-through is consistent with our firm-level evidence that expected profitability is not the sole driver of the investment response.

8 Using these Estimates to Infer MPIs in Other Datasets

Our estimates are obtained on Compustat, which covers publicly listed firms. These are larger and differently distributed across sectors than U.S. firms as a whole, so it is natural to ask what the average marginal propensity to invest would be in the population. This section answers that question by reweighting our sector estimates to the composition of U.S. firms reported in the Business Dynamics Statistics. The answer is that the population MPI is larger than the one we estimate on listed firms, and that this holds under each of the three definitions of a cell we report.

The exercise also provides a procedure for researchers who observe the composition of a population of firms but lack the long panel our estimator requires: our estimates by sector, together with counts of firms by sector, are enough to construct an average MPI for that population.

Where U.S. Firms Are. Table A14 reports the distribution of U.S. firms with at least five employees across sectors and employment categories. We consider the year 2023 to obtain an estimated MPI for a recent year. The population is mainly tertiary: 73.8 percent of firms with at least five employees are in wholesale trade, retail trade or services, against 5.9 percent in manufacturing, 4.0 percent in transportation and communications and 0.3 percent in mining.[12] It is also mainly small: firms with at least 1,000 employees account for 1.2 percent of the population. The Compustat sample is close to the reverse on both counts: manufacturing supplies the majority of firm-years, and roughly half of them are firms with at least 1,000 employees.

Imputation. We take the dimensions of heterogeneity observed both in Compustat and in the target dataset, attribute to every firm in the target the estimate obtained from Compustat firms in the same cell, and average using the number of firms in each cell as weights. Here the cells are defined by sector alone, and by sector interacted

[12]We restrict to firms with at least five employees because Compustat contains none below that size. In Compustat we use SIC codes, while in the BDS we observe NAICS codes. Our correspondence is as follows: mining is NAICS 21; manufacturing is NAICS 31-33; the tertiary sector is NAICS 42, 44-45, 54, 55, 56, 61, 62, 71, 72 and 81; transportation and communications is NAICS 48-49 and 51.

with employment or with age[13]. This requires assuming that publicly traded firms mostly differ from others by the sector in which they operate as well as their size and their age.

We retain mining, manufacturing, the tertiary sector, and transportation and communications, which together account for 84 percent of U.S. firms with at least five employees. Table 8 reports the result under three definitions of a cell: sectors alone, and sectors interacted with employment or with age.

Table 8: Imputed MPIs in the Population of U.S. Firms

		Sector ×	
	Sector	Employment	Age
Cells	4	8	8
Imputed MPI^{ε}	0.27	0.42	0.34
Imputed $MPI^{NPV^{\varepsilon}}$	0.17	0.26	0.21

Notes: Each firm in the Business Dynamics Statistics (U.S. Census Bureau 2023) is assigned the estimate obtained from the Compustat firms in the same cell, and the estimates are averaged using the number of firms in each cell as weights. The four sectors retained are mining, manufacturing, the tertiary sector, and transportation and communications; they account for 84 percent of U.S. firms with at least five employees in 2023, whose distribution is reported in Table A14. Employment is cut at 1,000 employees and age at 16 years, both boundaries of BDS categories.

Taking cells to be sectors, the imputed average MPI is 0.27, against 0.22 in the Compustat sample. Interacting sectors with employment gives 0.42 (Appendix Table A15) and with age 0.34 (Appendix Table A16). Every definition places the population figure above the Compustat one, between 0.27 and 0.42.

The population is concentrated in the tertiary sector and in small firms, and both raise the average MPI. The tertiary sector has the highest pass-through of the four, and it accounts for three quarters of U.S. firms with at least five employees against

[13]The two age measures are not perfectly comparable: the BDS records age from the birth of the firm in the Census data, whereas our measure begins at the earliest of first appearance in Compustat, CRSP or incorporation according to WorldScope. A firm that operated privately before listing is therefore younger in our data than in the BDS, so our young cell contains some mature firms while our old cell contains none that are genuinely young. Since older firms respond less, this attenuates the estimate we attribute to young firms in the population, and the age column is likely to understate the imputed MPI.

a minority of Compustat firm-years. Small firms respond more strongly than large ones as well. Reweighting toward the firms that dominate the economy therefore raises the average response.

The sector column is the most conservative of the three and the one whose inputs are all separately identified: the sales process, the pass-through and the capital-to-sales ratio are each estimated within the sector, as reported in Table 7. In the other two columns the sales process is estimated within the sector and held common to that sector's two cells, because it is not identified within the smaller cells on their own.

9 Conclusion

On average, firms respond significantly to a one-time, short-lived sales shock. In Compustat data, that is, among publicly listed U.S. firms, firms invest at least 22 cents out of an additional dollar of sales income caused by a transitory shock. A transitory shock does not raise contemporaneous sales income only, but also future sales income. Relating the investment response to the net present value of the whole sales stream, we find that firms invest at least 11 cents per dollar. Which of the two concepts is relevant depends on firms' access to finance: the contemporaneous measure for firms that cannot borrow against future sales; the net-present-value measure for those that can.

Different firms respond very differently, and the heterogeneity is sizable: younger firms, firms with fewer total assets, non-dividend-paying firms, and firms with fewer employees exhibit substantially higher MPIs, while their larger, older, and dividend-paying counterparts respond little and imprecisely. These patterns are consistent with the financial-frictions literature: firms that have not yet grown out of their constraints rely more heavily on internal resources to fund investment, making capital accumulation more sensitive to transitory income fluctuations. Sectors differ far more in their MPIs than in their pass-throughs: the elasticity of capital to a transitory shock lies between 0.47 and 0.71 in all four sectors, while the MPI ranges from 0.15 in manufacturing to 0.89 in mining. The difference comes almost entirely through capital intensity, mining and transport holding several times as much capital per dollar of sales as manufacturing or the tertiary sector.

Because small firms and firms in the tertiary sector are far more prevalent in the universe of firms than among publicly listed ones, we exploit this heterogeneity to impute the MPI beyond Compustat. Under the assumption that firms differ mainly along the observable dimensions we use (age, employment, and sector), we obtain an average MPI of 0.27 out of the current sales change, and of 0.17 out of the net present value of the sales change, among U.S. firms with at least five employees in the four sectors we estimate.

These findings speak directly to macroeconomic modeling. In the same way that business-cycle models target MPCs out of transitory shocks estimated from household-level data, we provide MPI estimates from firm-level data that heterogeneous-firm models can match. We also provide moments that discipline the shock process itself: the persistence, variance, and higher-order shape of transitory sales shocks.

They also carry policy implications. On the fiscal side, the aggregate investment response to a transfer program depends not only on its size but on which firms it reaches: transfers concentrated among younger, smaller, and non-dividend-paying firms generate a larger aggregate response. On the monetary side, our results offer a mechanism for the heterogeneous investment responses to monetary policy shocks documented in the empirical literature. The firm characteristics that predict stronger responses to monetary shocks are precisely those that predict higher MPIs in our framework, so part of the heterogeneous transmission of monetary policy operates through differences in how firms translate the general-equilibrium, cash-flow component of monetary shocks into investment.

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APPENDIX

A Additional Identification Results

A.1 Identification of the Income Process Parameters

We identify the MA coefficients θ of the transitory component, and the variance $\gamma_0 = E[\varepsilon^2] = \mathrm{Var}(\varepsilon)$, Pearson's moment coefficient of skewness $\gamma_1 = E[\varepsilon^3]/\sigma_\varepsilon^3 = E[\varepsilon^3]/\gamma_0^{3/2}$, and the excess kurtosis $\gamma_2 = E[\varepsilon^4]/\sigma_\varepsilon^4 - 3 = E[\varepsilon^4]/\gamma_0^2 - 3$ from the following moments

$$
\begin{aligned}
E[\Delta \ln(y_{i,t})\, \Delta \ln(y_{i,t+5})] &= -\,\mathrm{Var}(\varepsilon)\,\theta_4 && (24)\\
E[\Delta \ln(y_{i,t+1})\, \Delta \ln(y_{i,t+5})] &= -\,\mathrm{Var}(\varepsilon)\,\theta_4(\theta_1-1) + \mathrm{Var}(\varepsilon)(\theta_4-\theta_3) && (25)\\
E[\Delta \ln(y_{i,t+2})\, \Delta \ln(y_{i,t+5})] &= -\,\mathrm{Var}(\varepsilon)\,\theta_4(\theta_2-\theta_1) + \mathrm{Var}(\varepsilon)(\theta_4-\theta_3)(\theta_1-1) && (26)\\
&\quad + \mathrm{Var}(\varepsilon)(\theta_3-\theta_2)\\
E[\Delta \ln(y_{i,t+3})\, \Delta \ln(y_{i,t+5})] &= -\,\mathrm{Var}(\varepsilon)\,\theta_4(\theta_3-\theta_2) + \mathrm{Var}(\varepsilon)(\theta_4-\theta_3)(\theta_2-\theta_1) && (27)\\
&\quad + \mathrm{Var}(\varepsilon)(\theta_3-\theta_2)(\theta_1-1) + \mathrm{Var}(\varepsilon)(\theta_2-\theta_1)\\
E[\Delta \ln(y_{i,t+4})\, \Delta \ln(y_{i,t+5})] &= -\,\mathrm{Var}(\varepsilon)\,\theta_4(\theta_4-\theta_3) + \mathrm{Var}(\varepsilon)(\theta_4-\theta_3)(\theta_3-\theta_2) && (28)\\
&\quad + \mathrm{Var}(\varepsilon)(\theta_3-\theta_2)(\theta_2-\theta_1) + \mathrm{Var}(\varepsilon)(\theta_2-\theta_1)(\theta_1-1)\\
&\quad + \mathrm{Var}(\varepsilon)(\theta_1-1).\\
E\Big[(\Delta \ln(y_{i,t}))^2\, \Delta \ln(y_{i,t+5})\Big] &= -\mathrm{skew}(\varepsilon)\ \mathrm{Var}(\varepsilon)^{3/2}\,\theta_4 && (29)\\
E\Big[(\Delta \ln(y_{i,t}))^3\, \Delta \ln(y_{i,t+5})\Big] &= \big(\mathrm{kur}(\varepsilon) + 3 + 3\ \mathrm{Var}(\Delta \ln(y_{i,t}) - \varepsilon)\big)(-\theta_4)\ \mathrm{Var}(\varepsilon)^2, && \\
& && (30)\\
\mathrm{Var}(\Delta \ln(y_{i,t}) - \varepsilon) &= E\Big[(\Delta \ln(y_{i,t}))^2\Big] - \big(E[\Delta \ln(y_{i,t})]\big)^2 + \mathrm{Var}(\varepsilon). && (31)
\end{aligned}
$$

This gives us seven moments to identify seven parameters, the four MA coefficients plus the variance, skewness and kurtosis.

A.2 Identification of the iMPIs

We identify the effect of a transitory shock on log-capital growth at subsequent periods $t+s$: $\phi^{\varepsilon,Fs\Delta k} = \frac{\mathrm{Cov}(\Delta \ln k_{i,t+s}, \varepsilon_{i,t})}{\mathrm{var}(\varepsilon_{i,t})}$.

For $s = 0$, we keep our usual notation so $\phi^{\varepsilon,F0\Delta k} = \phi^{\varepsilon}$. To obtain the identification, we use our assumption that $\mathrm{Var}(\varepsilon_{i,t})$ is the same at all t. We then rely on the covariance between log-capital growth at t and log-sales growth at $t+s$ for $s \in \{1, \ldots, 5\}$

$$
\begin{aligned}
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+5}) &= -\theta_4 \phi^{\varepsilon} \mathrm{var}(\varepsilon) \\
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+4}) &= (\theta_4 - \theta_3)\phi^{\varepsilon} \mathrm{var}(\varepsilon) - \theta_4 \phi^{\varepsilon, F1\Delta k}\, \mathrm{Var}(\varepsilon) \\
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+3}) &= (\theta_3 - \theta_2)\phi^{\varepsilon} \mathrm{var}(\varepsilon) + (\theta_4 - \theta_3)\phi^{\varepsilon, F1\Delta k} \mathrm{var}(\varepsilon) - \theta_4 \phi^{\varepsilon, F2\Delta k} \mathrm{var}(\varepsilon) \\
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+2}) &= (\theta_2 - \theta_1)\phi^{\varepsilon} \mathrm{var}(\varepsilon) + (\theta_3 - \theta_2)\phi^{\varepsilon, F1\Delta k} \mathrm{var}(\varepsilon) + (\theta_4 - \theta_3)\phi^{\varepsilon, F2\Delta k} \mathrm{var}(\varepsilon) \\
&\quad - \theta_4 \phi^{\varepsilon, F3\Delta k} \mathrm{var}(\varepsilon) \\
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+1}) &= (\theta_1 - 1)\phi^{\varepsilon} \mathrm{var}(\varepsilon) + (\theta_2 - \theta_1)\phi^{\varepsilon, F1\Delta k} \mathrm{var}(\varepsilon) + (\theta_3 - \theta_2)\phi^{\varepsilon, F2\Delta k} \mathrm{var}(\varepsilon) \\
&\quad + (\theta_4 - \theta_3)\phi^{\varepsilon, F3\Delta k} \mathrm{var}(\varepsilon) - \theta_4 \phi^{\varepsilon, F4\Delta k} \mathrm{var}(\varepsilon).
\end{aligned}
$$

We also identify the effect of transitory shocks on the level of log-capital $\phi^{\varepsilon, Fsk} = \frac{\mathrm{Cov}(\ln k_{i,t+s}, \varepsilon_{i,t})}{\mathrm{var}(\varepsilon_{i,t})}$. For $s = 0$, we keep our usual notation so $\phi^{\varepsilon, F0k} = \phi^{\varepsilon}$. To obtain the identification, we use our assumptions that $\mathrm{var}(\varepsilon_{i,t})$ is the same at all t and that $\mathrm{Cov}(\ln k_{i,t},\, \varepsilon_{i,t-s})$ is the same at all t. We consider the same moments and use that, if $s \geq 1$

$$
\begin{aligned}
\phi^{\varepsilon, Fs\Delta k} \mathrm{var}(\varepsilon) &= \mathrm{Cov}(\Delta \ln k_{i,t},\, \varepsilon_{i,t-s}) = \mathrm{Cov}(\ln k_{i,t},\, \varepsilon_{i,t-s}) - \mathrm{Cov}(\ln k_{i,t-1},\, \varepsilon_{i,t-s}) \\
&= \phi^{\varepsilon, Fsk} \mathrm{var}(\varepsilon) - \phi^{\varepsilon, F(s-1)k} \mathrm{var}(\varepsilon).
\end{aligned}
$$

Rearranging, we obtain

$$
\begin{aligned}
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+5}) &= -\theta_4 \phi^{\varepsilon} \mathrm{var}(\varepsilon) \\
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+4}) &= (2\theta_4 - \theta_3)\phi^{\varepsilon} \mathrm{var}(\varepsilon) - \theta_4 \phi^{\varepsilon, F1k} \mathrm{var}(\varepsilon) \\
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+3}) &= (-\theta_4 + 2\theta_3 - \theta_2)\phi^{\varepsilon} \mathrm{var}(\varepsilon) + (2\theta_4 - \theta_3)\phi^{\varepsilon, F1k} \mathrm{var}(\varepsilon) \\
&\quad - \theta_4 \phi^{\varepsilon, F2k} \mathrm{var}(\varepsilon) \\
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+2}) &= (-\theta_3 + 2\theta_2 - \theta_1)\phi^{\varepsilon} \mathrm{var}(\varepsilon) + (-\theta_4 + 2\theta_3 - \theta_2)\phi^{\varepsilon, F1k} \mathrm{var}(\varepsilon) \\
&\quad + (2\theta_4 - \theta_3)\phi^{\varepsilon, F2k} \mathrm{var}(\varepsilon) - \theta_4 \phi^{\varepsilon, F3k} \mathrm{var}(\varepsilon) \\
\mathrm{Cov}(\Delta \ln k_{i,t},\, \Delta \ln y_{i,t+1}) &= (2\theta_1 - \theta_2 - 1)\phi^{\varepsilon} \mathrm{var}(\varepsilon) + (-\theta_3 + 2\theta_2 - \theta_1)\phi^{\varepsilon, F1k} \mathrm{var}(\varepsilon) \\
&\quad + (-\theta_4 + 2\theta_3 - \theta_2)\phi^{\varepsilon, F2k} \mathrm{var}(\varepsilon) + (2\theta_4 - \theta_3)\phi^{\varepsilon, F3k} \mathrm{var}(\varepsilon) \\
&\quad - \theta_4 \phi^{\varepsilon, F4k} \mathrm{var}(\varepsilon).
\end{aligned}
$$

The iMPIs are obtained by multiplying these values by the average capital to income ratio, in the same way we obtain contemporaneous MPIs from contemporaneous elasticities ϕ^{ε}.

B Sample Construction

B.1 Sample Selection

This section describes the construction of the dataset used in the analysis. We follow sample selection criteria that are standard in the literature (following the replication package of Ottonello and Winberry (2020)).

We restrict the sample to firms incorporated in the United States. We assign each firm to a broad sector using the first two digits of its SIC code, following the standard SIC division scheme. The categories are Agriculture, Forestry, and Fishing (SIC below 1000); Mining (1000–1499); Construction (1500–1799); Manufacturing (2000–3999); Transportation and Communications (4000–4899); Wholesale Trade (5000–5199); Retail Trade (5200–5999); and Services (7000–8999). We exclude three sectors: the financial sector (SIC 6000–6799), regulated utilities (SIC 4900–4999), and public administration (SIC 9100–9700).

We retain only firm-year observations in the period 1970-2019. We drop all firm-years before a firm's first observation of gross property, plant, and equipment (*PPEGT*) in the full annual Compustat dataset. We exclude firm-years in which acquisitions exceed 5% of total assets, as measured by the Compustat variable *AQC*. We trim the capital growth rate, sales growth rate, Tobin's Q, and the capital-to-sales ratio at the 1st and 99th percentiles of the annual distribution. We also drop firm-year observations where liquidity or leverage are outliers (negative liquidity ratio, leverage below -10 or above 10).

All nominal variables are deflated using the Implicit Price Deflator for the Nonfinancial Corporate Sector.

B.2 Variable Construction

The capital stock, denoted K_{it}, is constructed using a perpetual inventory method. We follow Ottonello and Winberry (2020) exactly, so that our estimates are comparable with that literature. This approach follows standard practice in the literature using Compustat data.

Firm size is measured by total assets. Leverage is defined as total debt divided by total assets, where total debt is the sum of debt in current liabilities and long-term debt. The liquidity ratio is cash and short-term investments divided by total assets. Sales are measured as net sales. Tobin's Q is the ratio of the market value of assets to book value. Firm age is constructed following Cloyne et al. (2023) using data from Thomson Reuters' WorldScope and the Center for Research in Security Prices (CRSP).

Table A1: Variable Definitions

Variable	Compustat Definition
Capital Stock	see text
Sales	SALE
Firm Size	log(AT)
Leverage	$(\texttt{DLC} + \texttt{DLTT})/\texttt{AT}$
Liquidity Ratio	CHE / AT
Tobin's Q	$(\texttt{AT} + \texttt{PRCCF} \times \texttt{CSHO} - \texttt{CEQ} + \texttt{TXDITC})/\texttt{AT}$
Dividend Payment	$\mathbf{1}[\texttt{DVC} > 0]$
Employment	EMP
Acquisitions	AQC / L.AT
Firm Age	min(Compustat first year, WorldScope incorporation year, CRSP first year)
Value Added	$\texttt{SALE} - \texttt{COGS}$
Cash Flow	$\texttt{IB} + \texttt{DP}$
OIBDP	OIBDP
EBITDA	$\texttt{SALE} - \texttt{COGS} - \texttt{XSGA}$

Following standard practice, we classify firms into eight broad sectors based on SIC codes: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation and communications; wholesale trade; retail trade; and services. We exclude finance, insurance, and real estate (SIC 6000–6799) and utilities (SIC 4900–4999).

C Additional Results

C.1 The Sales Process

Table A2: Covariances of Log-Sales Growth

	$\Delta y_{i,t}$	$\Delta y_{i,t+1}$	$\Delta y_{i,t+2}$	$\Delta y_{i,t+3}$	$\Delta y_{i,t+4}$	$\Delta y_{i,t+5}$	$\Delta y_{i,t+6}$
$\text{Cov}(\Delta y_{i,t}, \cdot)$	0.0634^{***}	-0.0114^{***}	-0.0041^{***}	-0.0026^{***}	-0.0014^{**}	-0.0026^{***}	0.0005
	(0.0019)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Observations	28,275	28,275	28,275	28,275	28,275	28,275	28,275

Notes: The sample is held constant across columns and contains only firm-year observations with non-missing sales growth in every year from t to $t+6$, so the 28,275 observations are identical in all columns and the estimates are directly comparable. Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Lower Bound Condition

Table A3: Pass-Through by Capital-to-Sales Ratio

	Capital-to-Sales Ratio	
	Low	High
Mean $\tilde{k}/\tilde{y}$	0.13	0.80
Pass-through ϕ^{ε}	0.36	0.59^{**}
	(0.22)	(0.24)
Observations	16,727	16,726

Notes: Standard errors in parentheses, clustered at the firm level. Split at the median of the lagged capital-to-sales ratio $\tilde{k}_{i,t-1}/\tilde{y}_{i,t-1}$. The ratio is lagged so that it is predetermined with respect to $\varepsilon_{i,t}$. The parameters of the sales process are held common across groups and estimated jointly, so differences in ϕ^{ε} reflect differences in the capital response per unit of an identically-defined shock. p-value for equality of ϕ^{ε}: 0.53. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The pass-through is higher among more capital-intensive firms (0.59 versus 0.36), implying a positive covariance. While we cannot reject a covariance of zero, the term is unlikely to move the average MPI far from the bound.

C.3 Permanent Component as an AR(1) Process

Table A4 reports the GMM estimates for $\rho \in \{0.99, 0.95, 0.94, 0.92\}$. At $\rho = 0.99$ the estimates coincide with the baseline. Pass-through and MPI rise monotonically as ρ falls, and the estimates lose precision, reaching 1.16 and 0.54 at $\rho = 0.92$.

Table A4: Pass-Through and MPI with an AR(1) Permanent Component

	$\rho = 0.99$	$\rho = 0.95$	$\rho = 0.94$	$\rho = 0.92$
Pass-through ϕ^{ε}	0.47^{***}	0.59^{***}	0.68^{***}	1.16^{*}
	(0.15)	(0.21)	(0.26)	(0.67)
MPI^{ε}	0.22^{***}	0.27^{***}	0.31^{***}	0.54^{*}
	(0.07)	(0.10)	(0.12)	(0.31)
Observations	33,453	33,453	33,453	33,453

Notes: Column ρ reports estimates obtained with the permanent component modeled as an AR(1) process with persistence ρ rather than a random walk. ρ is calibrated, not estimated, so the sample is identical across columns. Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 iMPIs

Table A5: Pass-Through of Transitory Sales Shocks to Current and Future Investment

Period forward s	0	1	2	3	4
Pass-through to growth $\phi^{\varepsilon,Fs\Delta k}$	0.47^{***}	-0.37	-0.09	0.52	0.96
	(0.15)	(0.27)	(0.34)	(0.39)	(0.65)
Pass-through to level $\phi^{\varepsilon,Fsk}$	0.47^{***}	0.11	0.02	0.55^{**}	1.50^{**}
	(0.15)	(0.18)	(0.25)	(0.27)	(0.61)
$MPI^{\varepsilon,Fsk}$	0.22^{***}	0.05	0.01	0.25^{**}	0.69^{**}
	(0.07)	(0.08)	(0.11)	(0.12)	(0.28)
Observations			33,453		

Notes: s indexes the horizon: $\phi^{\varepsilon,Fs\Delta k}$ is the pass-through of a transitory sales shock at t to capital growth at $t+s$, $\phi^{\varepsilon,Fsk}$ the pass-through to the capital level at $t+s$, and $MPI^{\varepsilon,Fsk}$ the corresponding change in the capital level scaled by the mean capital-to-sales ratio. The sample is identical across columns. Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.5 Robustness to Control Variables

Tables A6 and A7 examine the sensitivity of the baseline estimates to the progressive inclusion of control variables in the detrending step.

Table A6: Pass-Through and MPI: Robustness to Control Specification

		ϕ^{ε}	MPI^{ε}
(1)	year fixed effects + firm size	0.46^{**}	0.21^{**}
		(0.20)	(0.09)
(2)	+ leverage	0.49^{**}	0.22^{**}
		(0.21)	(0.09)
(3)	+ Tobin's Q	0.42^{*}	0.20^{*}
		(0.23)	(0.11)
(4)	+ age fixed effects	0.36^{*}	0.17^{*}
		(0.20)	(0.09)
(5)	+ industry fixed effects	0.39^{**}	0.18^{**}
		(0.20)	(0.09)
(6)	+ state fixed effects	0.39^{**}	0.18^{**}
		(0.19)	(0.09)
(7)	+ second lag (baseline)	0.47^{***}	0.22^{***}
		(0.15)	(0.07)
	Observations	33,453	

Notes: Each row adds the listed control to the specification in the row above; row (7) is the baseline specification. Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Specification (1) includes year fixed effects and firm size, and yields a pass-through of 0.46. Adding leverage in specification (2) leaves the estimate essentially unchanged at 0.49, and adding Tobin's Q in specification (3) lowers it to 0.42. Age fixed effects in specification (4) reduce the estimate to 0.36, its lowest value across the table, while industry and state fixed effects in specifications (5) and (6) return it to 0.39. Adding a second lag of the firm-level controls in the baseline specification (7) yields 0.47. All specifications are estimated on the same 33,453 firm-year observations, so the differences across rows reflect the controls alone and not changes in sample composition. The pass-through is statistically significant throughout, and the estimates lie between 0.36 and 0.49, a range that contains the baseline. The baseline is also the most precisely estimated.

Table A7 examines the sensitivity of our baseline estimates to alternative control specifications.

Table A7: Pass-Through and MPI: Robustness to Control Specification

		ϕ^{ε}	MPI^{ε}
(1)	baseline	0.47***	0.22***
		(0.15)	(0.07)
(2)	age + age^2	0.50***	0.23***
		(0.16)	(0.07)
(3)	+ size^2	0.49***	0.23***
		(0.16)	(0.07)
(4)	+ year $\times$ (leverage, size, Tobin's Q)	0.51***	0.23***
		(0.17)	(0.08)
(5)	+ year $\times$ (age, industry, state)	0.37*	0.17*
		(0.21)	(0.10)
(6)	+ second lag of the interactions	0.39*	0.18*
		(0.21)	(0.10)
(7)	+ dividend status	0.46***	0.21***
		(0.15)	(0.07)
	Observations	33,453	

Notes: Specification (1) is the baseline detrending: year, industry, state and age fixed effects, with once- and twice-lagged Tobin's Q, size and leverage. Each remaining specification modifies the baseline independently of the others, as described in its row. Specification (2) replaces the age fixed effects with a linear and quadratic age trend; (3) makes the same replacement and adds a quadratic in size; (4) interacts year with once-lagged size, leverage and Tobin's Q; (5) adds interactions of year with age, industry and state; (6) is (5) with the interacted controls entered at both lags; and (7) adds once- and twice-lagged dividend status. Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The baseline specification (1) includes year, industry, state, and age fixed effects, with once- and twice-lagged Tobin's Q, size, and leverage as controls. Each remaining specification augments the baseline with the controls listed in its row. Specifications (2) and (3) replace the age fixed effects with a linear and quadratic age trend, and additionally with a quadratic in size, leaving the pass-through at 0.50 and 0.49. Specification (4) lets the coefficients on size, leverage, and Tobin's Q vary by year and yields 0.51. Specification (5) further interacts year with age, industry, and state, which lowers the estimate to 0.37 and halves its precision; specification (6), which adds second lags of the same interactions, gives 0.39. Specification (7) adds lagged dividend status and yields 0.46. All specifications are estimated on the same 33,453 firm-year observations, so the differences across rows reflect the controls alone.

C.6 Robustness: Income Variable

Appendix Table A8 reports estimates obtained using alternative income measures. We consider three alternatives. Value added is constructed as sales minus cost of goods sold, and measures the firm's contribution to production net of intermediate inputs. Cash flow is net income plus depreciation. EBITDA is constructed as sales minus cost of goods sold minus selling, general and administrative expenses, capturing earnings before interest, taxes, depreciation, and amortization.

Both revenue-based measures are cleanly identified: income growth remains autocorrelated through the fifth lead. The earnings-based measures, however, are not: their growth rates lack the necessary autocovariance beyond the first lead, meaning we lack a strong instrument at the longer, uncontaminated horizons required for identification. We therefore report estimates for sales and value added only. We report sales as the baseline because it is the standard measure of firm resources in this literature and because the capital-to-sales ratio is the more interpretable scaling. Value added is closer than sales to the resources a firm can deploy, so a larger pass-through is what one would expect. The two specifications differ on both margins: the pass-through is 0.82 against 0.47, and the capital-to-income ratio is larger too, since value added is net of intermediate inputs.

Table A8: Robustness: Value Added as the Income Measure

	Sales (baseline)	Value Added
Pass-through ϕ^{ε}	0.47***	0.82**
	(0.15)	(0.35)
MPI^{ε}	0.22***	1.06**
	(0.07)	(0.45)
Observations	33,453	29,073

Notes: Standard errors in parentheses, clustered at the firm level. Both columns use the same MA(4) specification, instrumenting with the fifth lead of income growth, and the same set of controls in the detrending step. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Additional Heterogeneity Results

Table A9: Pass-Through and MPI by Firm Characteristics (Terciles)

	Age			Assets		
	Young	Middle	Old	Small	Middle	Big
Pass-through ϕ^{ε}	0.94***	0.27	0.17	0.87**	0.35	0.21
	(0.31)	(0.30)	(0.18)	(0.38)	(0.24)	(0.16)
MPI^{ε}	0.47***	0.12	0.08	0.31**	0.15	0.13
	(0.16)	(0.13)	(0.08)	(0.14)	(0.10)	(0.10)
Observations		33,453			33,453	
	Sales			Employment		
	Small	Middle	Big	Small	Middle	Big
Pass-through ϕ^{ε}	1.15***	0.19	0.08	1.31***	0.19	−0.12
	(0.40)	(0.20)	(0.14)	(0.45)	(0.18)	(0.14)
MPI^{ε}	0.58***	0.08	0.04	0.71***	0.08	−0.05
	(0.21)	(0.08)	(0.07)	(0.25)	(0.08)	(0.06)
Observations		33,453			32,877	

Notes: Standard errors in parentheses, clustered at the firm level. Tercile cutoffs: age, 17 and 32 years; lagged log real assets, 4.45 and 6.16; lagged log sales, 4.66 and 6.44; lagged log employment, -0.53 and 1.28. p-values from Wald tests on ϕ^{ε} *Age*: joint equality: 0.113; Young = Middle: 0.146; Young = Old: 0.037; Middle = Old: 0.790. *Assets*: joint equality: 0.291; Small = Middle: 0.276; Small = Big: 0.121; Middle = Big: 0.621. *Sales*: joint equality: 0.052; Small = Middle: 0.037; Small = Big: 0.015; Middle = Big: 0.652. *Employment*: joint equality: 0.010; Small = Middle: 0.022; Small = Big: 0.003; Middle = Big: 0.197. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Pass-Through and MPI by Leverage and Liquidity (Terciles)

	Leverage			Liquidity		
	Low	Middle	High	Low	Middle	High
Pass-through ϕ^{ε}	0.88***	0.20	0.34	0.17	0.11	1.15***
	(0.33)	(0.22)	(0.28)	(0.20)	(0.22)	(0.38)
MPI^{ε}	0.30***	0.08	0.21	0.09	0.05	0.42***
	(0.11)	(0.09)	(0.17)	(0.11)	(0.10)	(0.14)
Observations		33,453			33,451	

Notes: Standard errors in parentheses, clustered at the firm level. Lagged leverage tercile cutoffs: 0.11 and 0.29; lagged liquidity tercile cutoffs: 0.04 and 0.13. p-values from Wald tests on ϕ^{ε}. Leverage: joint equality: 0.254; Low = Middle: 0.099; Low = High: 0.236; Middle = High: 0.686. Liquidity: joint equality: 0.057; Low = Middle: 0.844; Low = High: 0.026; Middle = High: 0.023. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Pass-Through and MPI by Age × Size, Age × Dividend Status, and Age × Employment

	Age × Size (assets)			
	Young/Small	Young/Big	Old/Small	Old/Big
Pass-through ϕ^{ε}	1.10***	0.27	0.21	0.09
	(0.37)	(0.32)	(0.41)	(0.15)
MPI^{ε}	0.41***	0.18	0.08	0.04
	(0.14)	(0.22)	(0.16)	(0.07)
Observations	33,453			
	Age × Dividend Status			
	Young/No Div	Young/Div	Old/No Div	Old/Div
Pass-through ϕ^{ε}	1.21***	0.31	0.44	0.00
	(0.42)	(0.26)	(0.49)	(0.16)
MPI^{ε}	0.56***	0.16	0.18	0.00
	(0.19)	(0.14)	(0.20)	(0.07)
Observations	33,425			
	Age × Size (employment)			
	Young/Small	Young/Big	Old/Small	Old/Big
Pass-through ϕ^{ε}	1.25***	0.09	0.37	−0.08
	(0.42)	(0.21)	(0.44)	(0.15)
MPI^{ε}	0.63***	0.04	0.18	−0.03
	(0.21)	(0.09)	(0.22)	(0.06)
Observations	32,877			

Notes: Standard errors in parentheses, clustered at the firm level. Age is split at the median (cutoff: 24 years); size is split at the median of lagged log real assets (cutoff: 5.30, ≈\$200M) in the first panel and of lagged log employment (cutoff: 0.39) in the third; dividend status uses lagged payment status. p-values from Wald tests on ϕ^{ε} *Age × Size (assets)*: joint equality: 0.106; Young: Small = Big: 0.108; Old: Small = Big: 0.797; Small: Young = Old: 0.119; Big: Young = Old: 0.611; Young/Small = Old/Big: 0.014; Young/Big = Old/Small: 0.901. *Age × Dividend Status*: joint equality: 0.061; Young: No Div = Div: 0.075; Old: No Div = Div: 0.398; No Div: Young = Old: 0.244; Div: Young = Old: 0.329; Young/No Div = Old/Div: 0.008; Young/Div = Old/No Div: 0.804. *Age × Size (employment)*: joint equality: 0.032; Young: Small = Big: 0.015; Old: Small = Big: 0.332; Small: Young = Old: 0.161; Big: Young = Old: 0.506; Young/Small = Old/Big: 0.004; Young/Big = Old/Small: 0.556. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.1 Within-Group Sales Process

Table A12: Pass-Through and MPI Across Firm Characteristics

	Assets		Employment		Sales	
	Small	Big	Small	Big	Small	Big
Shock process	$MA(4)$	$MA(4)$	$MA(4)$	$MA(3)$	$MA(4)$	$MA(4)$
Pass-through ϕ^{ε}	0.54***	0.29	0.55***	0.24	0.57***	0.21
	(0.19)	(0.26)	(0.17)	(0.19)	(0.19)	(0.22)
MPI^{ε}	0.20***	0.16	0.28***	0.10	0.27***	0.09
	(0.07)	(0.14)	(0.09)	(0.08)	(0.10)	(0.10)
Observations	15,857	17,596	14,918	21,030	15,640	17,813

	Age		Dividend Status	
	Young	Old	No Div.	Div.
Shock process	$MA(4)$	$MA(4)$	$MA(4)$	$MA(4)$
Pass-through ϕ^{ε}	0.68***	0.19	0.51***	0.36
	(0.22)	(0.22)	(0.17)	(0.35)
MPI^{ε}	0.34***	0.08	0.23***	0.17
	(0.11)	(0.10)	(0.08)	(0.16)
Observations	14,489	18,964	14,271	19,154

	Liquidity		Leverage	
	Low	High	Low	High
Shock process	$MA(4)$	$MA(4)$	$MA(4)$	$MA(4)$
Pass-through ϕ^{ε}	0.40	0.50***	0.42***	0.63
	(0.26)	(0.18)	(0.15)	(0.40)
MPI^{ε}	0.21	0.20***	0.15***	0.36
	(0.14)	(0.07)	(0.05)	(0.23)
Observations	17,371	16,080	16,997	16,456

Notes: Standard errors in parentheses, clustered at the firm level. Splits at the median of the lagged variable: assets; employment; sales; age; liquidity; leverage. Dividend status is a lagged zero-one indicator. Medians are computed on the estimation sample. Each group is estimated on its own subsample, so that the variance and persistence of the transitory shock, and the order of the moving-average process, may differ between the two groups being compared; the order is reported in each panel. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Sectors

Table A13: The Transitory Sales Process by Sector

	Mining	Manufacturing	Tertiary	Transport
Order	$MA(4)$	$MA(4)$	$MA(3)$	$MA(1)$
θ_1	0.61***	0.50***	0.36***	0.34***
	(0.05)	(0.03)	(0.05)	(0.07)
θ_2	0.30***	0.32***	0.24***	—
	(0.05)	(0.03)	(0.04)	
θ_3	0.28***	0.16***	0.08**	—
	(0.05)	(0.03)	(0.04)	
θ_4	0.19***	0.07***	—	—
	(0.04)	(0.02)		
var(ε)	0.063	0.037	0.022	0.013
	(0.007)	(0.003)	(0.003)	(0.003)
NPV^{ε}	2.32	2.01	1.66	1.34
Observations	1,833	19,860	10,879	3,519

Notes: Estimates are obtained by running the GMM specification separately on each sector subsample. $NPV^{\varepsilon} = 1 + \sum_{s=1}^{k} \theta_s (1+r)^{-s}$ with $r = 0.02$ is the net present value of a transitory shock raising current sales by one dollar. The tertiary sector pools wholesale trade, retail trade and services. Standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Application to the Business Dynamics Statistics (BDS)

Table A14: Where the Population of U.S. Firms Is

	Employment		
	$< 1{,}000$	$\geq 1{,}000$	All
Share of all U.S. firms with five or more employees			
Mining	0.32	0.01	0.32
Manufacturing	5.78	0.11	5.89
Tertiary	72.92	0.86	73.78
Transport and communications	3.92	0.11	4.04
Others	15.84	0.13	15.97
All sectors	98.77	1.23	100.00
Weights used in the imputation			
Mining	0.39	0.01	0.40
Manufacturing	6.88	0.14	7.01
Tertiary	86.80	1.03	87.82
Transport and communications	4.67	0.14	4.81
All four sectors	98.73	1.31	100.00

Notes: Percentages of U.S. firms with at least five employees in 2023, from the Business Dynamics Statistics (U.S. Census Bureau 2023). The row 'Others' collects construction, agriculture, utilities, finance and real estate. The lower block rescales the shares of the four sectors we estimate to sum to one.

Table A15: Pass-Through and MPI by Employment, across Sectors

Sector	Mining		Manufacturing		Tertiary		Transport	
Employment	Small	Big	Small	Big	Small	Big	Small	Big
Shock process	$MA(4)$		$MA(4)$		$MA(3)$		$MA(1)$	
Pass-through ϕ^{ε}	0.42	0.31	1.29**	-0.27	0.89	0.59	1.62*	0.33
	(0.27)	(0.25)	(0.50)	(0.18)	(1.05)	(0.39)	(0.97)	(0.21)
MPI^{ε}	1.00	0.39	0.41**	-0.08	0.36	0.19	1.60*	0.32
	(0.64)	(0.32)	(0.16)	(0.06)	(0.42)	(0.13)	(0.96)	(0.21)
Observations	1,011	778	9,059	10,562	3,891	6,744	873	2,549
Share of U.S. firms (%)	0.4	0.0	6.1	0.1	87.6	0.9	4.8	0.1

Notes: Standard errors in parentheses, clustered at the firm level. Employment is split at 1,000 employees, using the lagged value; firm-years for which employment is not reported are excluded. The variance and persistence of the transitory shock, and the order of the moving-average process, are estimated on the whole sector and held common to that sector's two cells, so that only the pass-through and the MPI vary within a sector. Share of U.S. firms is the percentage of firms with at least five employees in that cell in the 2023 Business Dynamics Statistics, among the four sectors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Pass-Through and MPI by Age, across Sectors

Sector	Mining		Manufacturing		Tertiary		Transport	
Age	Young	Old	Young	Old	Young	Old	Young	Old
Shock process	$MA(4)$		$MA(4)$		$MA(3)$		$MA(1)$	
Pass-through ϕ^{ε}	0.71**	0.36*	1.21**	0.20	1.01	0.52	1.28**	0.33
	(0.36)	(0.22)	(0.55)	(0.24)	(0.81)	(0.55)	(0.60)	(0.38)
MPI^{ε}	1.61*	0.61*	0.40**	0.06	0.39	0.18	1.23**	0.33
	(0.83)	(0.37)	(0.19)	(0.07)	(0.31)	(0.18)	(0.58)	(0.38)
Observations	589	1,244	5,889	13,971	4,291	6,588	1,243	2,276
Share of U.S. firms (%)	0.2	0.1	3.2	3.1	57.8	30.7	3.3	1.6

Notes: Standard errors in parentheses, clustered at the firm level. Age is split at 16 years, using the lagged value. Note that this split at 16 is different from our previous age split. It is chosen to better match the age distribution in the BDS. The variance and persistence of the transitory shock, and the order of the moving-average process, are estimated on the whole sector and held common to that sector's two cells, so that only the pass-through and the MPI vary within a sector. Share of U.S. firms is the percentage of firms with at least five employees in that cell in the 2023 Business Dynamics Statistics, among the four sectors. Age is measured from the first year in which the firm appears in Compustat, Worldscope or CRSP, whereas the BDS measures it from the birth of the firm in the Census data. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.