Online Appendix

Can Capital Adjustment Costs Explain the Decline in Investment-Cash Flow Sensitivity?

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Abstract

This Online Appendix contains results and technical details that are referred to but not reported in detail in the main manuscript. In Section OA1, we demonstrate the derivation of the empirical counterpart of the Euler investment equation, whereas the evidence regarding the increase in the adjustment costs based on industry-level data is presented in Section OA2. Section OA3 contains a firm-level data analysis of the differences in the evolution of I-CF sensitivity between developed and developing countries as well as between high-tech and non high-tech firms, in which the cross-sectional variation of the levels of knowledge capital stock is exploited.

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OA 1 Euler equation: Empirical counterpart

The empirical counterpart of the Euler investment equation is derived as follows. The firm aims to maximize the expected discounted value of the net profit stream:

$$V(A_t, K_t) = \max_{\{K_{\tau+1}, I_\tau\}_{\tau=t}^{\infty}} E_t \sum_{\tau=t} \left(\frac{1}{1+r}\right)^{\tau-t} [\Pi(A_\tau, K_\tau) - I_\tau - G(I_\tau, K_\tau) - H(X_\tau, K_\tau)], \tag{OA 1.1}$$

subject to $I_t = K_{t+1} - (1-\delta)K_t$. All functions are as previously defined. The Lagrangian with multiplier q_τ is given by

$$\begin{aligned} \mathcal{L} \;=\; & \max_{\{K_{\tau+1}, I_\tau\}_{\tau=t}^{\infty}} E_t \sum_{\tau=t} \left(\frac{1}{1+r}\right)^{\tau-t} [\Pi(A_\tau, K_\tau) - I_\tau - G(I_\tau, K_\tau) \\ & -H(X_\tau, K_\tau) + q_\tau(I_\tau + (1-\delta)K_\tau - K_{\tau+1})], \end{aligned} \tag{OA 1.2}$$

where q_t is the shadow price of capital. The first-order conditions with respect to I_t and K_{t+1} are, respectively,

$$\frac{\partial \mathcal{L}}{\partial I_t} = 0 \Rightarrow q_t = 1 + \frac{\partial G(I_t, K_t)}{\partial I_t} + \frac{\partial H(X_t, K_t)}{\partial I_t}, \tag{OA 1.3}$$

$$\begin{aligned} & \frac{\partial \mathcal{L}}{\partial K_{t+1}} = 0 \Rightarrow \\ & q_t = \frac{1}{1+r} E_t \left[(1-\delta)q_{t+1} + \frac{\partial \Pi(A_{t+1}, K_{t+1})}{\partial K_{t+1}} - \frac{\partial G(I_{t+1}, K_{t+1})}{\partial K_{t+1}} - \frac{\partial H(X_{t+1}, K_{t+1})}{\partial K_{t+1}}\right]. \end{aligned} \tag{OA 1.4}$$

With the iterative substitution of (OA 1.4) and the transversality condition which requires that $\lim_{T\to\infty} q_{t+T}/(1+r)^{t+T} = 0$, we obtain

$$q_t = E_t \sum_{\tau=t+1}^{\infty} \frac{(1-\delta)^{\tau-t-1}}{(1+r)^{\tau-t}} \left(\frac{\partial \Pi(A_\tau, K_\tau)}{\partial K_\tau} - \frac{\partial G(I_\tau, K_\tau)}{\partial K_\tau} - \frac{\partial H(X_\tau, K_\tau)}{\partial K_\tau} \right). \qquad \text{(OA 1.5)}$$

The substitution of (OA 1.3) into (OA 1.4) yields

$$\begin{aligned}
&1 + \frac{\partial G(I_t, K_t)}{\partial I_t} + \frac{\partial H(X_t, K_t)}{\partial I_t} = \\
&\frac{1}{1+r} E_t \left[(1-\delta) \left(1 + \frac{\partial G(I_{t+1}, K_{t+1})}{\partial I_{t+1}} + \right.\right. \\
&\left.\left. \frac{\partial H(X_{t+1}, K_{t+1})}{\partial I_{t+1}} \right) + \frac{\partial \Pi(A_{t+1}, K_{t+1})}{\partial K_{t+1}} - \frac{\partial G(I_{t+1}, K_{t+1})}{\partial K_{t+1}} - \frac{\partial H(X_{t+1}, K_{t+1})}{\partial K_{t+1}} \right]. \qquad \text{(OA 1.6)}
\end{aligned}$$

When constructing the empirical equation, we assume that the production function displays constant returns to scale in a perfectly competitive output market so that $\partial\Pi(A_t, K_t)/\partial K_t = \Pi_t/K_t$. Assuming further the quadratic adjustment cost function, we obtain $\partial G(I_t, K_t)/\partial I_t = \gamma I_t/K_t$ and $\partial G(I_t, K_t)/\partial K_t = -0.5\gamma\,(I_t/K_t)^2$. Also $\partial H(X_t, K_t)/\partial I_t = b\phi(I_t/K_t - \Pi_t/K_t)$ and $\partial H(X_t, K_t)/\partial K_t = -0.5b\phi\,(I_t K_t - \Pi_t/K_t)\,(I_t K_t + \Pi_t/K_t)$. Adding an expectation error ϵ_{t+1} where $E_t(\epsilon_{t+1}) = 0$ to remove the expectation operator, we arrive at the empirical counterpart of the Euler equation:

$$\begin{aligned}
&\frac{1}{1+r} \left[(1-\delta) \left(1 + \gamma \left(\frac{I_{t+1}}{K_{t+1}} \right) + b\phi \left(\frac{I_{t+1}}{K_{t+1}} - \frac{\Pi_{t+1}}{K_{t+1}} \right) \right) + \right. \\
&\left. \frac{\Pi_{t+1}}{K_{t+1}} + \frac{1}{2}\gamma \left(\frac{I_{t+1}}{K_{t+1}} \right)^2 + \frac{1}{2} b\phi \left(\frac{I_{t+1}}{K_{t+1}} - \frac{\Pi_{t+1}}{K_{t+1}} \right) \left(\frac{I_{t+1}}{K_{t+1}} + \frac{\Pi_{t+1}}{K_{t+1}} \right) \right] + \epsilon_{t+1} \\
&= 1 + \gamma \left(\frac{I_t}{K_t} \right) + b\phi \left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t} \right). \qquad \text{(OA 1.7)}
\end{aligned}$$

OA 2 Evidence based on industry-level data

Following the strand of literature that relates adjustment costs to the productivity growth, we adopt the approach of Bessen (2002) and estimate the trend of adjustment costs with 4-digit SIC code industry-level data from NBER-CES Manufacturing Industry Database for period 1977-2011. The adjustment cost is defined as the deviation of the actual output from potential output. For each industry j, the actual output is $Y_t = Y_t^*(1 - G_t)$, with potential output being equal to $Y_t^* = A_t K_t^{\alpha_{K,t}} M_t^{\alpha_{M,t}} L_t^{\alpha_{L,t}}$. Here, A_t denotes productivity shock, M_t (L_t) is material (labor) input, $\alpha_{K,t}$ ($\alpha_{M,t}$, $\alpha_{L,t}$) is the elasticity of output with respect to capital (material, labor). $G_t = \gamma I_{t-1}/K_{t-1}$ is the adjustment cost per unit of potential output, which is linearly related to the lagged investment-to-capital ratio. $1-G_t$ is analogous to the speed of adjustment (SOA), as in the partial adjustment model of Lintner (1956). For the industry j at time t, we transform levels into logarithms, take the differences and rearrange $Y_{jt} = Y_{jt}^*(1 - G_{jt})$ to obtain ($\widehat{\cdot}$ denotes a log change):

$$\widehat{Z_{jt}} \equiv \widehat{Y_{jt}} - \alpha_{K,jt}\widehat{K_{jt}} - \alpha_{M,jt}\widehat{M_{jt}} - \alpha_{L,jt}\widehat{L_{jt}} = \widehat{A_{jt}} - \gamma\Delta\frac{I_{jt-1}}{K_{jt-1}}. \qquad \text{(OA 2.1)}$$

Parameter γ can be estimated by regressing $\widehat{Z_{jt}}$ on the lagged change of investment-to-capital ratio, $\Delta(I_{j,t-1}/K_{j,t-1})$. In order to infer the time-series pattern of adjustment costs, we include the period trend variable T which equals 1 for 1977-1981, 2 for 1982-1987 and so on. Table OA1 presents the regression output for the pattern of adjustment costs. The coefficient of $T \times \Delta(I_{j,t-1}/K_{j,t-1})$ shows that the adjustment cost parameter increases by 0.053 (0.052 with industry fixed effects) in each period when time fixed effects are not included and by

TABLE OA1
Adjustment to the potential output level

Regression output based on data from NBER-CES Manufacturing Industry Database covering periods between 1977 and 2011. The dependent variable is productivity residual growth $\widehat{Z_{jt}}$ as described in Bessen (2002). The explanatory variables are lagged change of investment-to-capital ratio $\Delta\frac{I_{j,t-1}}{K_{j,t-1}}$, interaction term between period trend variable T, lagged change of investment-capital ratio and, depending on specification, industry and year fixed effects (FE). Period trend variable is defined as 1 in 1977-1981 and 2 in 1982-1986 and so forth. Standard errors are clustered in industry level and reported in the parentheses. Adjusted R^2 (R_a^2) is also reported. The number of observations is 15,953. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Variables	Dependent variable is $\widehat{Z_{jt}}$		
$\Delta\frac{I_{j,t-1}}{K_{j,t-1}}$	-0.094	-0.099	-0.196^{**}
	(0.085)	(0.098)	(0.087)
$T \times \Delta\frac{I_{j,t-1}}{K_{j,t-1}}$	-0.053^{**}	-0.052^{***}	-0.015
	(0.019)	(0.021)	(0.019)
Industry FE	N	Y	Y
Year FE	N	N	Y
R_a^2	0.015	0.014	0.127

0.015 (although not statistically significant at standard levels) once they are added. Even though the upward trend of adjustment costs is less pronounced when aggregate shocks are controlled for, the coefficient of $T \times \Delta(I_{j,t-1}/K_{j,t-1})$ has the expected sign, consistent with an increase in adjustment costs.

OA 3 Firm-level data cross-sectional evidence

To provide an additional set of tests, we exploit the cross-sectional variation in the level of knowledge capital stock as the foundation for capital adjustment costs. Specifically, we perform the analysis along the lines of Moshirian et al. (2017), who investigate differences in I-CF sensitivity patterns between developing and developed economies, as well as compare the trends of I-CF sensitivity between high-tech and non high-tech industries. To the extent that increasing capital adjustment costs can be a consequence of knowledge capital accumulation, we expect that countries that are more equipped to adopt the new technology (i.e., developed countries) or industries that rely more on advanced technology (i.e., high-tech industries) exhibit a more pronouced rise in capital adjustment costs and thereby a stronger decline in I-CF sensitivity.

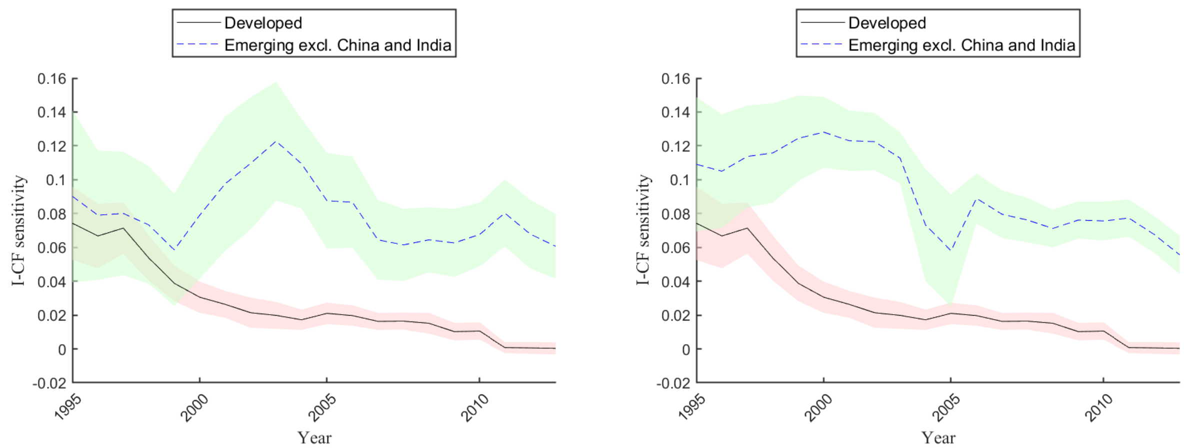
OA 3.1 Cross-country regression results

Moshirian et al. (2017) examine the difference in I-CF sensitivities between firms from developed economies and those from developing countries. They demonstrate that the decrease in I-CF sensitivity is quite substantial for the former group and only moderate for the latter. It is argued that the declining importance of the productivity of tangible assets combined with a reduction in income predicability leads to the decreasing pattern of I-CF sensitivity in the "new economy". We replicate the OLS analysis of Moshirian et al. (2017) and complement it with the GMM5 approach. As in Moshirian et al. (2017), we estimate the time-series trend of I-CF sensitivity for developed countries (excluding the U.S.) and emerging economies (excluding China and India).[1] The level of a country's economic development is defined according to the MSCI classification. We estimate coefficients of investment on cash flow over a rolling window of 5 years for both sets of economies. As q is more likely to be measured with error for this international sample, we apply an additional filter and remove the observations where its magnitude exceeds 100 or is below 0. We begin from year 1995 to ensure that there are at least 200 observations each year for each developing country.

[1] The exclusion of China and India is motivated by Moshirian et al. (2017) as driven by their fast pace of adopting new technologies, which makes them less comparable with other developing countries.

FIGURE OA1
Investment-cash flow sensitivity of developed economies vs. developing countries

OLS GMM5



I-CF sensitivity estimates based on the ordinary least squares (OLS), and Erickson-Whited error-corrected estimator (GMM5). The solid black line shows the estimates for developed economies excluding the U.S. and the dashed blue line shows the estimates of I-CF sensitivity for emerging countries excluding China and India. Shaded areas represent confidence intervals at the 95% level.

We present the rolling-window estimated coefficients in Figure OA1.

The decline of I-CF sensitivity for developing countries is less steep than for developed economies. Based on the OLS analysis, we conclude that I-CF sensitivity is declining over time in advanced economies but remains flat and does not drop until the most recent periods in developing countries. The decreasing trend of I-CF sensitivity for developed economies and the absence of such a clear decline for less developed economies are still visible when the error-corrected estimator GMM5 is used (the right panel of Figure OA1). The estimated I-CF sensitivity in developed economies starts from 0.07 in 1995-2000 and drops to near zero in 2010-2018 for GMM5 estimator. The estimate of I-CF sensitivity for the GMM5 estimator in less developed economies fluctuates around 0.10 until almost 2003 before it experiences a slight reduction.

We provide an alternative to Moshirian et al.'s (2017) explanation for the observed difference in I-CF sensitivities between developed economies and developing economies based on the implications of capital adjustment costs. Firms in developed countries are faster in adopting knowledge capital and hence should experience a more rapid increase in their capital adjustment costs year on year. Therefore, their I-CF sensitivities decline substantially, also when the productivity of physical capital, as proxied by q, is fully controlled for and the measurement error in q is corrected for. Firms in the developing economies, however, face a more moderate pace of technological change and, hence, a slower increase in their capital adjustment costs. Therefore, their I-CF sensitivities decline at a lower pace or face no decline at all, at least until recently.

OA 3.2 Cross-industry regression results

In the second part of the cross-sectional analysis, we classify manufacturing firms into belonging to either non-high-tech or high-tech industries. According to Chen and Chen's (2012), high-tech firms are those with SIC codes 3840-3849, 3820-3829, 3670-3679, 3660-3669, 3570-3579, and 2830-2839. Within each industry group, we run the baseline regression (1) for 9 periods from 1977-1981 to 2017-2019. As high-tech firms are likely to accumulate knowledge capital more quickly compared to non high-tech groups, we expect that the former experience a more rapid increase in capital adjustment costs over time and, therefore, a steeper decline in I-CF sensitivity.

Table OA2 shows a decreasing pattern of I-CF sensitivity regardless of the industry group the firms belong to. It also demonstrates that I-CF sensitivity for the high-tech industries

TABLE OA2
Estimation across industry groups

Estimation results for the baseline I-CF regression for two industry groups. Columns 2 and 4 (3 and 5) report coefficients β_1 of q (β_2 of cash flow) for two industry groups: high-tech and non high-tech, respectively. The p value for the null hypothesis that the coefficients are the same between the first period and the last period is reported below. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Period	High-tech: β_1	β_2	Non high-tech: β_1	β_2
1977-1981	0.032***	0.276***	0.015***	0.268***
1982-1986	0.022***	0.113***	0.021***	0.144***
1987-1991	0.017***	0.054***	0.013***	0.062***
1992-1996	0.011***	0.044***	0.010***	0.049***
1997-2001	0.006***	0.013*	0.011***	0.036***
2002-2006	0.006***	−0.001	0.007***	0.017*
2007-2011	0.006***	−0.002	0.008***	0.001
2012-2016	0.004***	−0.006	0.004***	0.009
2017-2019	0.002***	−0.007	0.005	0.010
p value	0.000	0.000	0.000	0.000

has declined in 2000s more rapidly than for other industries. For the former group, I-CF sensitivity starts to disappear and becomes statistically not significant in 2002-2006. It also remains lower in the most recent sample periods compared to the non high-tech group. In order to quantify the magnitude of the difference in the decline of I-CF sensitivity between high-tech and non high-tech industries, we estimate β_2 by year and regress it on the natural logarithm of the year trend variable T, which is equal to 1 for 1977, 2 for 1978 and so on. Table OA3 shows that I-CF sensitivity drops by on average 8.6% every year for the high-tech group whereas it decreases by only 7% for the non high-tech group. The reported t-statistics and the corresponding p-values for the null hypothesis that the declining trend of β_2 is the same for high-tech and non high-tech groups indicate that the declining trend of β_2 is significantly more prominent for the high-tech firms than that for their non high-tech counterparts.

TABLE OA3
Comparison of the trend in β_2 across industry groups

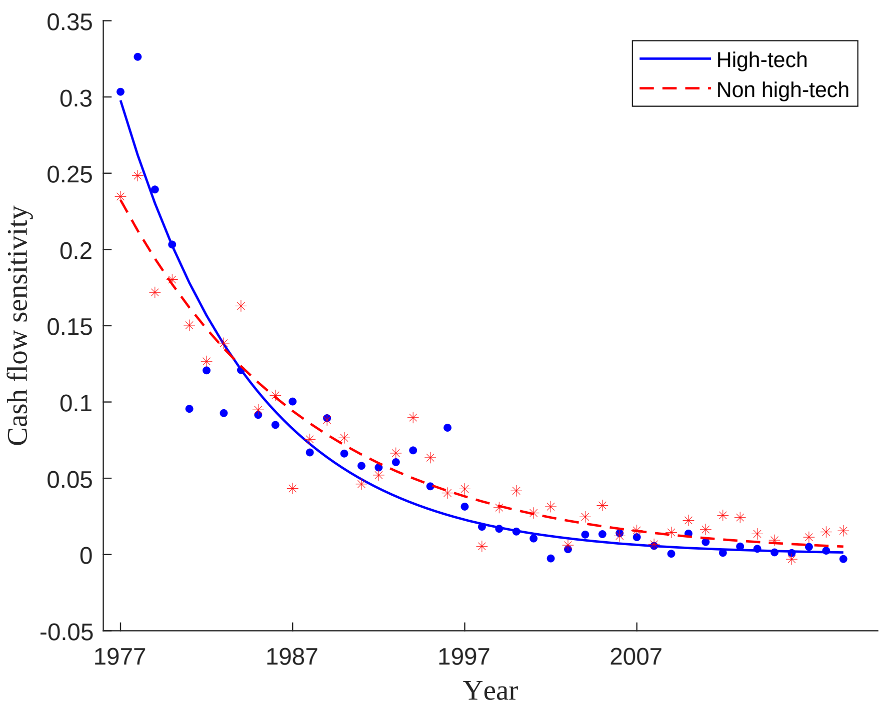
Estimates of the declining trend for β_2 across both industry groups, i.e., high-tech and non high-tech. The model is estimated by regressing β_2 on the natural log of year trend variable T, which is equal to 1 for 1977, 2 for 1978 and so on. Standard errors are shown in parentheses. t-statistics and corresponding p-values for the null hypothesis that the declining trend is the same between high-tech and non high-tech sectors are reported. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	β_2 high-tech	β_2 non high-tech	
$\log(T)$	-0.086^{***}	-0.070^{***}	
	(0.004)	(0.003)	
H0: Coeff. high-tech = coeff. non high-tech			
t-stat.:	-3.005	p-value:	0.000

The comparison of the declining trends is further illustrated in Figure OA2 with scatter plots and exponential curve fitting. It shows that high-tech firms have experienced a more substantial decline in their I-CF sensitivities, which is consistent with the view that they are more affected by the increasing costs of capital adjustment due to their higher pace of knowledge capital accumulation.

FIGURE OA2
Investment-cash flow sensitivity across groups by year (fitted with an exponential curve)

High-tech vs. non high-tech



Scatter plots of investment-cash flow sensitivities estimated for firms in high-tech (solid blue) vs. non high-tech (dashed red) industries fitted with an exponential curve.

OA References

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