Panel Data Analysis

Econometrics A

Ass. Prof. Amine Ouazad

References

- William H. Greene, Chapter on Models for Panel Data.

- Quarterly Journal of Economics, "Managing with Style: The Effect of Managers on Firm Policies", November 2003.

Outline

1. Panel data examples
2. Cross-section vs longitudinal analysis
3. Fixed effects estimation
   - OLS, within, first-differenced estimator
4. Random effects estimation
5. Hausman test
6. Tricky questions
7. Two way fixed effects regression

PANEL DATA EXAMPLES

Panel data examples

- Active workers followed term after term. Labor Force Survey.
  - Calculation of the unemployment rate.
- Families' purchasing decision followed over multiple weeks.
  - Consumer Expenditure Survey.
- Firms' share prices/earnings/ accounting measures.
  - Compustat + Execucomp.

Panel data notation

- i: individual, firm, “unit” of analysis.
- t: time period. Either minute, day, hour, week, year, etc.
- Sometimes individuals/firms are grouped into units.
  - J(i,t): firm of employee i at time t.

Cross section vs longitudinal data analysis

- In cross-sectional regressions, individuals differ both in their covariates and in constant unobservable dimensions.
- In longitudinal regressions, where changes in the outcome variable are related to changes in the covariates, the non time-varying unobservables are captured.

Usefulness of panel data analysis

1. Capture non-time varying unobservables.
2. Correct for individual or time-specific unobserved shocks.
3. Estimate non-time varying unobservables, their correlation with observables, their significance.

FIXED EFFECTS ESTIMATION

Fixed effects estimation

$$y_{i,t} = x'_{i,t}\beta + \alpha_i + \varepsilon_{i,t}$$

- with xit a K-vector of observables.
- Stacking observations together:

$$\mathbf{y_i} = \mathbf{X_i}\beta + \mathbf{i} \cdot \alpha_i + \varepsilon_i$$

- yi: T-vector of dependent variable.
- Xi: TxK matrix of covariates for individual i.
- **i**: a T-vector of ones.

- Fixed effect αi captures the constant unobservables: solution for the omitted variable bias, if the omitted variable is constant.

Balanced panel data

- **Balanced panel data:**
  - Same number of time periods T of observation for each individual i=1,2,..,N.
- **Unbalanced panel data:**
  - At least one individual is observed for a different number of time periods.
  - Ti : number of observations for individual i.
- Checking in Stata: using **xtset.**

- If Ti is random (non correlated with epsilon i), then the unbalancedness is not an issue. Most results of this session apply.
- If Ti is nonrandom, there is either:
  - endogenous entry into the dataset.
  - Or endogenous exit (**attrition**) out of the dataset.
- Then specific theory needs to be developed (out of the scope of the current session).

Matrix form

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{D}\alpha + \varepsilon$$

- X is an NT times K matrix.
- D is an NT times N matrix, the design matrix.
- alpha: an N–vector of fixed effects.
- The constant is either in X, and then D drops one effect, or the constant is in D, and then X has no constant. The former is the typical convention.

OLS Dummy variables

- The simplest way to estimate is to include one dummy variable per individual.
- Requires that $E(\varepsilon_i|i,x_{it}) = 0$.
- In Stata: xi: regress consumption income i.individual
- But:
  - It is computationally very costly: the number of variables is K + the number of individuals.
    - Inverting the variance covariance matrix is very costly.
  - The consistency of the estimator of beta cannot be proved for N-> infinity as the number of variables also tends to infinity.

Transformations

- Trick is to transform the regression to make it (i) simpler to estimate (ii) simpler to prove the consistency of the estimator of beta.

1. first difference
2. within difference

Assumptions

- Strict exogeneity
  - $E(\varepsilon_{it} \mid x_{i1}, \ldots, x_{iT}) = 0$
  - Note the difference with the standard A3 in OLS.
- Homoskedasticity (in this session, but can be lifted) A4.
- And of course A1, A2.

First-differenced estimator

$$y_{i,t} - y_{i,t-1} = (x_{i,t} - x_{i,t-1})'\beta + \varepsilon_{i,t} - \varepsilon_{i,t-1}$$

- Note that strict exogeneity implies that A3 is satisfied for this first-differenced regression.
- Noting Δ the first-differenced estimator.

$$\Delta \mathbf{y_i} = \Delta \mathbf{x_i}'\beta + \Delta \varepsilon_\mathbf{i}$$

- In vector form.

First-differenced estimator

$$b_W = (X'\Delta'\Delta X)^{-1} X'\Delta'\Delta Y$$

- First-differenced estimator is CAN under strict exogeneity.
- However it is not BLUE as first-differencing introduces AR correlations between residuals.
- Write the best estimator as an exercise.

Within estimator

$$y_{i,t} - \overline{y_{i,\cdot}} = (x_{i,t} - \overline{x_{i,\cdot}})\beta + \varepsilon_{i,t} - \overline{\varepsilon_{i,\cdot}}$$

- Notice again that strict exogeneity implies that A3 is satisfied for the within regression.
- Again, noting W the within transformation.

$$W\mathbf{y_i} = W\mathbf{x_i}\beta + W\varepsilon_i$$

Within estimator of β

$$b_W = (X'W'WX)^{-1}X'W'WY$$

- The within estimator b_W is a CAN estimator of β under strict exogeneity (and other maintained assumptions).
- However notice that bw is not BLUE. The most efficient estimator is the GLS estimator (rarely used, but write it as an exercise).

Implementation

- xtset individual time
- xtreg y x1 ... xK, fe
  for the within transformation
- xtreg y x1 ... xK, fd
  for the first-differenced transformation

- The two estimators should not be statistically different.

Asymptotic equivalence

- Under the assumption of strict exogeneity, both estimators are consistent estimators of beta.
  - plim b_{within} = plim b_{fd}.
- If the strict exogeneity assumption is violated, then the 2 estimators differ asymptotically.
- Except for T=2, where they are equal for any dataset. (prove this)

A2 Full rank assumption

- If a variable does not vary over time, then its first-difference or its within transformations are zero, and the effect of the variable cannot be estimated.
- A2 requires (X'W'WX) or (X'Δ'ΔX) to be invertible, or (for OLS dummy variable estimator), no vector in X to be perfectly correlated with D.

Effect of constant covariates

- 2 step regression:
  - Estimate the fixed effects model.
    - xtreg y x1 ... xK , fe
  - Predict the fixed effects.
    - predict effect, d
  - Regress the predicted fixed effects on the constant covariates.
    - regress effect z1 ... zK .
- But!
  - this assumes that z1 ... zK are orthogonal to the non time-varying unobservables
  - we never assumed that x1 ... xK was orthogonal to the effect.

Do not

- Perform the transformation yourself and report the standard errors of the regression.
  - The s.e.s would be wrong.
- Rather, let stata do the correction on the standard errors for you.

IV regression and fixed effects

- IV estimation can be combined with a fixed effect regression.
- IV will take care (if valid) of the time-varying unobservables.
- Hence IV needs to be time varying.
- Stata command xtivreg/xtivreg2.

Fixed effects regression and measurement error

- Fixed effects regression tends in general to magnify measurement error.
- In the first-differenced estimator:
  - The variance of the first-differenced transformation is typically smaller than the variance of the levels. Exercise.
- In the within estimator:
  - The variance of the within-transformed covariates is smaller than the original variance. Exercise.

RANDOM EFFECTS ESTIMATION

Random effects estimation

$$y_{i,t} = x'_{i,t}\beta + (\alpha + u_i) + \varepsilon_{i,t}$$

- where u_i is an iid draw from a normal distribution with mean α and with variance σ_u^2.
- The constant is either in x, or as the mean of u.

Random effects interpretation

- Captures unobserved shocks common to an individual.
- The shock for individual i is not estimated, only the variance of the shocks.
- The shocks are independent of the covariates.

GLS estimation

- Random effects estimation amounts to GLS estimation. The variance-covariance matrix needs to be estimated.
- By block:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_\varepsilon^2 + \sigma_u^2 & \sigma_u^2 & \sigma_u^2 & \cdots & \sigma_u^2 \\ \sigma_u^2 & \sigma_\varepsilon^2 + \sigma_u^2 & \sigma_u^2 & \cdots & \sigma_u^2 \\ & \cdots & & & \\ \sigma_u^2 & \sigma_u^2 & \sigma_u^2 & \cdots & \sigma_\varepsilon^2 + \sigma_u^2 \end{bmatrix} = \sigma_\varepsilon^2 \mathbf{I}_T + \sigma_u^2 \mathbf{i}_T \mathbf{i}_T',$$

GLS estimation

- Variance-covariance matrix.

$$\mathbf{\Omega} = \begin{bmatrix} \mathbf{\Sigma} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{\Sigma} & \mathbf{0} & \cdots & \mathbf{0} \\ & & & \vdots & \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{\Sigma} \end{bmatrix}$$

- Estimator:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{\Omega}^{-1}\mathbf{y}$$

- And (after calculations)

$$\mathbf{\Sigma}^{-1/2} = \frac{1}{\sigma_\varepsilon}\left[\mathbf{I} - \frac{\theta}{T}\mathbf{i}_T\mathbf{i}_T'\right]$$

GLS and FGLS

- However neither the variance of the residuals nor the variance of the shocks are known.
- The first-differenced or the within transformation gives the standard deviation of the residual of the equation.
- The variance of the OLS regression gives the sum of the variance of the random effect and the sum of the variance of the residual.

$$\text{plim } s^2_{Pooled} = \text{plim } \frac{\mathbf{e}'\mathbf{e}}{nT - K - 1} = \sigma^2_\varepsilon + \sigma^2_u.$$

Why use random effects?

- Random effects do not control for endogenous unobservables.
- Random effects require strict exogeneity of the shock, and hence orthogonality with the covariates.
- Fixed effects allow for a correlation between the effect and the covariates.
- Why use random effects?
  - The variance of the fixed effects is not consistently estimated.
  - If the covariates and the random effects are orthogonal, random effect estimation is more efficient.

HAUSMAN TEST

Hausman test

- Hausman test compares the coefficient estimates for the covariates in the fixed effects framework and in the random effects framework:
- Null hypothesis: $b_{FE} = b_{RE}$.
- If the orthogonality of the covariates and of the effects is true (under H0), then both estimators are consistent and converge to the same value β.
- Under H0, the random effects estimator is more efficient (i.e. has smaller variance) than the fixed effects estimator.

Same logic as for the IV OLS hausman test

- The statistic:

$$W = \chi^2[K-1] = [\mathbf{b} - \hat{\boldsymbol{\beta}}]' \hat{\boldsymbol{\Psi}}^{-1} [\mathbf{b} - \hat{\boldsymbol{\beta}}].$$

- follows a chi-squared distribution with K-1 degrees of freedom.

Implementation

- Reported by xtreg, re.
- Otherwise use “estimates store” and “hausman”.
- In practice report the Hausman test if using either random effects or fixed effects.

TWO WAY FIXED EFFECTS (ABOWD, KRAMARZ, MARGOLIS, 1999)

Two way fixed effects

- Estimate the contribution of the industry, the firm, the CEO to firm performance/the CEO's wage.
- Example: "Managing with style", by Marianne Bertrand.

Two way fixed effects specification

$$y_{i,t} = \theta_i + \psi_{J(i,t)} + \varepsilon_{i,t}$$

- θ_i: the individual effect.
- $\Psi_{J(i,t)}$: the firm effect.

- Covariates can be added.

Matrix notation

$$Y = D\theta + F\psi + \varepsilon$$

- where D is the design matrix for the individual effects, F is the design matrix for the firm effects.

Two options

- Either estimate the model as a model with two random effects, but with orthogonal effects.
  - Advantage: easier to estimate, efficient if orthogonality is true. Estimate of the variances is unbiased.
  - Problem: orthogonality is equivalent to random assignment (plausible?) and effects cannot be estimated one by one.
- Fixed effects estimation.

Projection on the worker dimension

- Noting M_D the projection on the worker dimension, then:

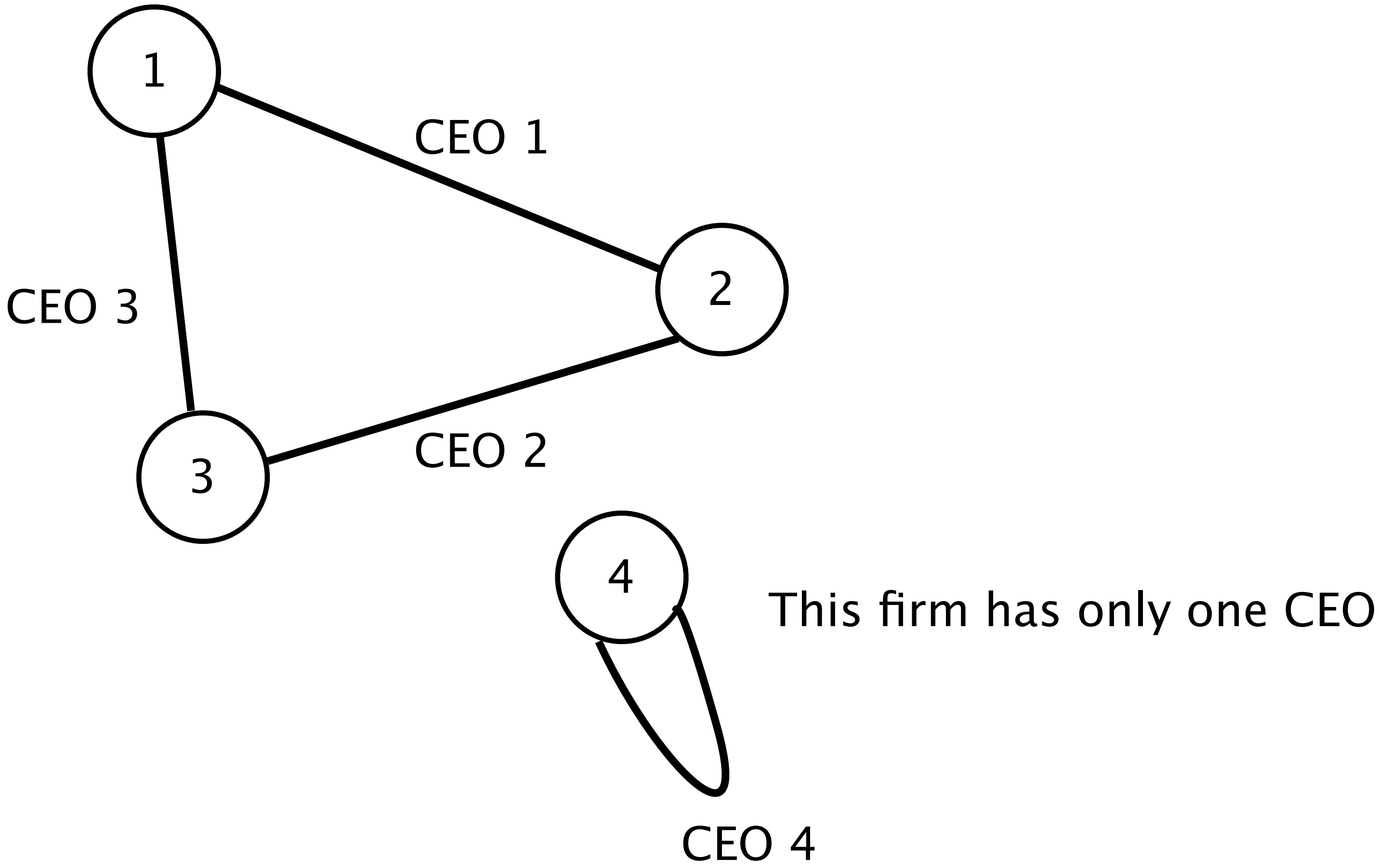
- Estimator of Ψ
$= (F'(1-M_D)F)^{-1} F'(1-M_D)Y$

- As the number of individuals per firm converges to infinity, the vector of firm effects is a consistent estimator of the firm effects.

Identification of the firm effects

- After a bit of algebra, it can be shown that:
- Estimator of Ψ
  = (1-mobility matrix)$^{-1}$ times a vector
- Where the mobility matrix has the empirical probability of moving from one firm to another.
- Using the Frobenius-Perron theorem, 1-mobility matrix is invertible if the mobility graph of firms is connex.

Non connex graph of firms



Projection on the worker dimension

- Similarly:

- Estimator of θ
  $= (D'(1-M_F)D)^{-1} D'(1-M_F)Y$

Identification of the worker effects

- Typically issue is that the number of observations per worker is small and does not converge to infinity.
- Estimate is unbiased but not consistent.
- Variance of the estimate of the individual effect is approximately given by the CLT.

Implementation of the identification test

- ssc install a2group
- a2group, individual(ceoid) unit(firmid) generate(group)

Estimation of the two way fixed effects model.

- ssc install a2reg.
- Make sure no variable is missing.
- a2reg y x1 ... xK, individual(ceoid) unit(firmid)
- Standard errors:
  bootstrap, n(10): a2reg y x1 ... xK, individual(ceoid) unit(firmid).

Estimation of the two way fixed effects model.

- Alternative: OLS with dummies.

- xi: regress y x1 .... xK i.ceoid i.firmid

- Gives standard errors in one step.
- But the variance-covariance matrix has dimension K+# of CEOS+# of firms !

Threats to identification

- Correlation between the mobility of a CEO from one firm to another firm and the unobservable time-varying shocks.
- If good CEOs tend to move to firms that experience an upward trend in their performance, the difference between good and bad CEOs will be overestimated.
- If good CEOs tend to move to firms that experience a downward trend in their performance, the difference between good and bad CEOs will be underestimated.

THE

QUARTERLY JOURNAL
OF ECONOMICS

Vol. CXVIII November 2003 Issue 4

MANAGING WITH STYLE: THE EFFECT OF MANAGERS ON FIRM POLICIES*

MARIANNE BERTRAND AND ANTOINETTE SCHOAR

This paper investigates whether and how individual managers affect corporate behavior and performance. We construct a manager-firm matched panel data set which enables us to track the top managers across different firms over time. We find that manager fixed effects matter for a wide range of corporate decisions. A significant extent of the heterogeneity in investment, financial, and organizational practices of firms can be explained by the presence of manager fixed effects. We identify specific patterns in managerial decision-making that appear to indicate general differences in "style" across managers. Moreover, we show that management style is significantly related to manager fixed effects in performance and that managers with higher performance fixed effects receive higher compensation and are more likely to be found in better governed firms. In a final step, we tie back these findings to observable managerial characteristics. We find that executives from earlier birth cohorts appear on average to be more conservative; on the other hand, managers who hold an MBA degree seem to follow on average more aggressive strategies.

TABLE I
DESCRIPTIVE STATISTICS

	Manager-firm matched sample		Manager characteristics sample		Compustat	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Total sales	5606.5	11545.6	5333.3	10777.4	2649.6	5878.2
Investment	0.39	2.94	0.28	0.50	0.34	2.67
Average Tobin's Q	2.40	3.85	2.03	2.05	1.70	1.43
Cash flow	0.44	1.91	0.45	2.10	0.43	2.47
N of acquisitions	0.77	1.48	0.65	1.40	0.36	1.45
Leverage	0.35	0.39	0.34	0.28	0.45	1.21
Interest coverage	35.0	875.1	40.5	663.1	27.6	166.2
Cash holdings	0.11	0.16	0.08	0.11	0.17	0.80
Dividends/earnings	0.11	0.79	0.14	1.05	0.16	0.25
N of diversifying acquisitions	0.32	1.09	0.28	0.91	0.12	0.63
R&D	0.05	0.07	0.04	0.14	0.03	0.06
Advertising	0.05	0.06	0.05	0.06	0.04	0.06
SG&A	0.26	0.98	0.21	0.19	0.18	0.64
Return on assets	0.16	0.11	0.19	0.15	0.10	0.09
Operating return on assets	0.09	0.12	0.11	0.22	0.08	0.13
Sample size	6766		10472		38489	

a. "Manager-firm matched sample" refers to the set of firm-year observations for firms that have at least one manager observed in multiple firms with at least a three-year stay at each firm. This sample includes observations for these firms in the years in which they have other managers that we do not observe in multiple firms (see subsection III.A for details). "Manager characteristics sample" refers to the set of firm-year observations for which we can obtain information on the year of birth and educational background of the CEO (see subsection VI.A for details). "Compustat" is a comparison sample of the 1500 largest listed firms over the period 1969 to 1999. All samples exclude firms in the banking and insurance industry, as well as regulated industries.

b. Details on the definition and construction of the variables reported in the table are available in the Data Appendix.

c. Total sales are expressed in 1990 dollars.

d. Sample size refers to the maximum number of observations; not all variables are available for each year and firm.

TABLE II
Executive Transitions between Positions and Industries

to:	CEO	CFO	Other
from:			
CEO	117	4	52
	63%	75%	69%
CFO	7	58	30
	71%	71%	57%
Other	106	0	145
	60%		42%

a. This table summarizes executives' transitions across positions and industries in the manager-firm matched panel data set (as described in subsection III.A and Table I). All transitions are across firms. The first entry in each cell reports the number of transitions from the row position to the column position. The second line in each cell reports the fraction of the transitions in that cell that are between different two-digit industries.

b. "Other" refers to any job title other than CEO or CFO.

More specifically, for each dependent variable of interest, we propose to estimate the following regression:

$$y_{it} = \alpha_t + \gamma_i + \beta X_{it} + \lambda_{CEO} + \lambda_{CFO} + \lambda_{Others} + \epsilon_{it}, \qquad (1)$$

where y_{it} stands for one of the corporate policy variables, α_t are year fixed effects, γ_i are firm fixed effects, X_{it} represents a vector of time-varying firm level controls, and ϵ_{it} is an error term. The remaining variables in equation (1) are fixed effects for the managers that we observe in multiple firms. Because we want to separately study the effect of CEOs, CFOs, and other top executives on corporate policies, we create three different groups of manager fixed effects: λ_{CEO} are fixed effects for the group of managers who are CEOs in the last position we observe them in, λ_{CFO} are fixed effects for the group of managers who are CFOs in the last position we observe them in, and λ_{Others} are fixed effects for the group of managers who are neither CEOs nor CFOs in the last position we observe them in.[17] Finally, when estimating equation (1), we account for serial correlation by allowing for clustering of the error term at the firm level.[18]

TABLE III
Executive Effects on Investment and Financial Policies

Panel A: Investment policy

	F-tests on fixed effects for				
	CEOs	*CFOs*	*Other executives*	*N*	*Adjusted* R^2
Investment				6631	.91
Investment	16.74 (<.0001, 198)			6631	.94
Investment	19.39 (<.0001, 192)	53.48 (<.0001, 55)	8.45 (<.0001, 200)	6631	.96
Inv to *Q* sensitivity				6631	.95
Inv to *Q* sensitivity	17.87 (<.0001, 223)			6631	.97
Inv to *Q* sensitivity	5.33 (<.0001, 221)	9.40 (<.0001, 58)	20.29 (<.0001, 208)	6631	.98
Inv to CF sensitivity				6631	.97
Inv to CF sensitivity	2.00 (<.0001, 205)			6631	.98
Inv to CF sensitivity	0.94 (.7276, 194)	1.29 (.0760, 55)	1.28 (.0058, 199)	6631	.98
N of acquisitions				6593	.25
N of acquisitions	2.01 (<.0001, 204)			6593	.28
N of acquisitions	1.68 (<.0001, 199)	1.74 (.0006, 55)	4.08 (<.0001, 203)	6593	.36

Panel B: Financial policy

	F-tests on fixed effects for				
	CEOs	*CFOs*	*Other executives*	*N*	*Adjusted* R^2
Leverage				6563	.39
Leverage	0.99 (.5294, 203)			6563	.39
Leverage	0.86 (.9190, 199)	1.43 (.0225, 54)	1.21 (.0230, 203)	6563	.41
Interest coverage				6278	.31
Interest coverage	0.56 (.99, 193)			6278	.31
Interest coverage	0.35 (.99, 192)	13.85 (<.0001, 50)	2.61 (<.0001, 192)	6278	.41
Cash holdings				6592	.77
Cash holdings	2.52 (<.0001, 204)			6592	.78
Cash holdings	2.48 (<.0001, 201)	3.68 (<.0001, 54)	2.53 (<.0001, 202)	6592	.80
Dividends/earnings				6580	.65
Dividends/earnings	5.78 (<.0001, 203)			6580	.71
Dividends/earnings	4.95 (<.0001, 199)	1.07 (.3368, 54)	1.74 (<.0001, 203)	6580	.72

TABLE VI
Size Distribution of Manager Fixed Effects

	Median	Standard deviation	25th percentile	75th percentile
Investment	0.00	2.80	−0.09	0.11
Inv to Q sensitivity	−0.02	0.66	−0.16	0.12
Inv to CF sensitivity	0.04	1.01	−0.17	0.28
N of acquisitions	−0.04	1.50	−0.54	0.41
Leverage	0.01	0.22	−0.05	0.09
Interest coverage	0.00	860.0	−56.0	51.7
Cash holdings	0.00	0.06	−0.03	0.02
Dividends/earnings	−0.01	0.59	−0.13	0.11
N of diversifying acquis.	−0.04	1.05	−0.28	0.21
R&D	0.00	0.04	−0.10	0.02
SG&A	0.00	0.66	−0.09	0.09
Advertising	0.00	0.04	−0.01	0.01
Return on assets	0.00	0.07	−0.03	0.03
Operating return on assets	0.00	0.08	−0.02	0.03

a. The fixed effects used in this table are retrieved from the regressions reported in Tables III and IV (row 3).

b. Column 1 reports the median fixed effect for each policy variable. Column 2 reports the standard deviation of the fixed effects. Columns 3 and 4 report the fixed effects at the twenty-fifth percentile and seventy-fifth percentile of the distribution, respectively.

c. Each fixed effect is weighted by the inverse of its standard error to account for estimation error.

In practice, we propose to estimate regressions as follows:

$$F.E.(y)_j = \alpha + \beta F.E.(z)_j + \epsilon_j, \tag{2}$$

where j indexes managers, and y and z are any two corporate policy variables. Note that the right-hand-side variable in equation (2) is an estimated coefficient which is noisy by definition. This will lead to a downward bias in an OLS estimation of β. Since we know the precision with which the fixed effects are measured, we use a GLS estimation technique to account for the measurement error in the right-hand-side variable. We weigh each observation by the inverse of the standard error on the independent variable, which we obtain from the first step regressions.[29]

TABLE VII
Relationship between the Manager Fixed Effects

	Investment	Inv to Q	Inv to CF	Cash holdings	Leverage	R&D	Return on assets
Investment							0.00
							(0.00)
Inv to Q sensitivity	**6.8**						**0.03**
	(0.92)						**(0.01)**
Inv to CF sensitivity	0.02	**−0.23**					−0.01
	(0.6)	**(0.11)**					(0.01)
Cash holdings	−1.10	−0.79	−0.46				**−0.12**
	(1.62)	(1.71)	(1.72)				**(0.05)**
Leverage	−0.39	−0.28	−0.63	**−0.40**			−0.02
	(0.55)	(0.59)	(0.60)	**(0.17)**			(0.02)
R&D	**0.07**	**0.08**	**−0.03**	**−0.23**	**−0.02**		0.11
	(0.00)	**(0.02)**	**(0.01)**	**(0.04)**	**(0.01)**		(0.11)
Advertising	0.01	**0.02**	−0.01	−0.01	0.00	0.25	**0.31**
	(0.01)	**(0.01)**	(0.01)	(0.04)	(0.01)	(0.15)	(0.15)
N of acquisitions	**−0.27**	0.08	**0.23**	**0.01**	**0.02**	**−0.01**	**−0.01**
	(0.11)	(0.10)	**(0.10)**	**(0.00)**	**(0.01)**	**(0.00)**	**(0.00)**
N of divers. acquis.	**−0.30**	−0.14	0.14	0.01	0.01	**−0.01**	**−0.01**
	(0.13)	(0.15)	(0.14)	(0.01)	(0.02)	**(0.00)**	**(0.00)**
SG&A	**−0.22**	**−0.30**	**0.10**	0.54	0.06	**−4.32**	**−3.36**
	(0.01)	**(0.04)**	**(0.03)**	(0.56)	(0.21)	**(0.90)**	**(0.62)**

a. Each entry in this table corresponds to a different regression.

b. Each entry reports the coefficient from a weighted regression of the fixed effects from the row variable on the fixed effects from the column variable. Observations in these regressions are weighted by the inverse of the standard error on the independent variable.

c. Coefficients that are significant at the 10 percent level are highlighted in bold.