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IDENTIFICATION OF THE EQUILIBRIUM EXCHANGE RATE PASS-THROUGH EFFECT IN COINTEGRATED VAR WITH AN APPLICATION TO THE EURO AREA*

IGOR MASTEN[1]

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ABSTRACT: *The exchange rate pass-through is of considerable importance for policy makers in open economies. Based on work of Johansen (2002) this paper develops the conditions for the identication of equilibrium pass-through effect in cointegration framework. In addition, I specify the restrictions for testing the perfect equilibrium pass-through. The method is illustrated on the Euro area data and the pass-through effect of the Euro effective exchange rate. The results show that conditional on the type of economic shocks that lead to a permanent change in the exchange rate, the equilibrium pass-through effect can be both very low and high.*

Keywords: *exchange rate pass-through effect, identification, cointegration analysis*

JEL Classification: E42, E52, E58, C32

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1. Introduction

Exchange rate pass-through is defined as the change in prices caused by the change in the nominal exchange rate. The pass-through effect operates broadly through three basic channels: (1) a direct effect through prices of imported goods in the CPI; (2) an effect through prices of imported intermediate goods; and (3) an effect through price setting and expectations that include also the expected responses of monetary policy (Garcia and Restrepo, 2001). Estimation of pass-through effect leads to important policy implications in the choice of exchange rate regimes. At the same time, it represents a significant challenge in empirical work.

The literature has developed two broad approaches to estimation of exchange rate pass-through effect. The first approach is based on single-equation estimation in large cross-country panels. A notable example are Campa and Goldberg (2002) (see also Campa and Goldberg, 2005) who estimate a simple single-equation model for 25 OECD countries over the period 1975 to 1999 and measure the pass-through effect (to import prices) with the coefficient on the nominal exchange rate. Goldfajn and Werlang (2000) study the relationship between exchange rate depreciations and inflation for 71 countries in the period 1980 to 1998. Choudhri and Hakura (2001) extend the study of Goldfajn and Werlang (2000) and try to establish the role of the exchange rate regime in determining the extent of pass-through in 71 countries in the period 1979 to 2000. Single equation approach is used also by Darvas (2001) and Mihaljek and Klau (2008) who study emerging economies.

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1 The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Bank of Slovenia.

VAR pass-through is typically measured by means of impulse responses of prices to an identified exchange rate shock.[2] The problem with such an approach approach is that it gives only a partial estimate of pass-through. As shown by Corsetti and Dedola (2005) we can observe as many (different) measures of pass-through effect as there are identified structural shocks. Concentrating on price responses only to an exogenous exchange rate shock neglects other sources of stochastic variation in the nominal exchange rate and prices. In addition, exchange rate changes need not occur only as consequences of stochastic shocks, but they can also reflect systematic changes in policy like the change in the inflation target. All such changes are not accounted for in a typical SVAR analysis.

This paper draws on Coricelli et al. (2006) and considers the estimation of pass-through effect with the cointegrated vector autoregression model (CVAR). Such an approach has a number of important advantages. Price series are commonly integrated at least of order one, which calls for an explicit test for cointegration. From an economic point of view, neglecting cointegration is surprising since long-run co-movement of prices and exchange rate is borne out by theory. Neglecting cointegration when it is genuinely present means neglecting the intrinsic meaning of equilibrium long-run relationship between the nominal exchange rate and prices.

CVAR methodology has been used in previous studies (see for example Kim, 1998; Billmeier and Bonato, 2002; Babecka-Kucharcukova, 2009 and Beirne and Bijsterbosch, 2009). These studies, however, do not discuss the issue of interpretation of cointegration coefficients as in Johansen (2002), which implies that the estimates of the pass-through presented in these studies may not be properly identified. Lack of identification means that cointegration coefficient estimates cannot be interpreted as equilibrium coefficients of pass-through.

This paper contributes to the literature by developing the criteria for identification of equilibrium exchange rate pass-through within the cointegration framework. I show that identification depends on cointegration rank. Moreover, the estimated cointegration rank suggest how many other endogenous variables, in addition to prices, are affected by a permanent change in the exchange rate. For instance, the extent of exchange rate pass-through to prices may differ if we allow for accompanying equilibrium changes in output or in interest rates, which is in line with the theoretical analysis of Corsetti and Dedola (2005). In the first case we measure the effect of the exchange rate on prices conditional on a permanent real shocks, while in the second conditional on a financial shock. Finally, I show how the proposed identification framework can be used to test for perfect exchange rate pass-through.

The method is illustrated on the Euro area data. The Euro area case is interesting from the point of view of unconventional monetary policy measures initiated by the European central bank in the fall of 2014 with important expected effects operating through the exchange rate channel. The empirical analysis in the paper shows that pass-through of the Euro effective exchange rate to consumer prices is the highest in case of exchange rate changes accompanied by long-run changes in real output. In such a case, the test cannot reject the hypothesis of a perfect pass-through. Conditional on equilibrium changes in interest rates (financial shock) or foreign prices (nominal shock) the extent of exchange rate pass-through is limited.

The paper proceeds as follows. Section 2 discusses the theoretical conditions for identification of the exchange rate pass-through effect in a cointegrated VAR model. Section 3 presents the empirical results, while Section 4 concludes.

[2] A different use of SVAR analysis is found in Choudri, Faruqee and Hakura (2002). Their empirically observed impulse responses of prices to an exchange rate shock are used not to measure pass-though directly but as a benchmark for simulated responses obtained from calibrated theoretical model under different assumptions about nominal rigidities in the economy.

2. Identification of equilibrium exchange rate pass-through effect

This section presents the analysis of the equilibrium exchange rate pass-through effect to (consumer) prices within the cointegration framework. Compared to existing studies of pass-through the analysis introduces two novelties. First, within I(1) cointegration analysis the paper offers a formal discussion of identification of pass-through effect conditional on cointegration rank. Secondly, I show that the equilibrium measure of the pass-through effect may not be unique and discuss what equilibrium changes of other endogenous variable under analysis accompany different measures of exchange rate pass-through. These changes are related to the conventional long-run identification restrictions for identification of structural shocks commonly employed in the structural VAR literature.

To facilitate the analysis consider a system of variables (1) in which the effect of the nominal exchange rate on prices is analyzed taking into account the endogenous dynamics in, foreign prices, output and the interest rate differentials:

$$X_t = (p_t, e_t, p_t^*, i_t - i_t^*, y_t). \tag{1}$$

where y_t denotes output, e_t is the nominal exchange rate, p_t are domestic prices, p_t^* foreign prices and $i_t - i_t^*$ the nominal interest rate differential between the domestic and the foreign economy. Such a system of variables is considered also in the empirical analysis of this paper and is motivated by standard macroeconomic theory. Domestic prices, the nominal exchange rate and foreign prices are related through the (relative) purchasing power relation. The interest rate differential affects exchange rate dynamics through the interest rate parity. Finally, output captures the effect of real factors on all endogenous variables in the system. Moreover, it is typically of interest to evaluate also the effect of exchange rate changes on output.

The variables are modelled as a cointegrated VAR

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Phi D_t + \varepsilon_t \tag{2}$$

with a corresponding reduced rank condition $\Pi = \alpha\beta'$(see Johansen (1995) for a detailed presentation). The matrix β contains the cointegrating relations and α contains the corresponding loading coefficients. The cointegration coefficient between the exchange rate and prices is of central interest because we need establish under what conditions it can be interpreted as equilibrium pass-through effect. A cointegration relation containing e_t and p_t can be generically written in regression format as follows

$$p_t = \beta_1 e_t + \beta_2 p_t^* + \beta_3 (i_t - i_t^*) + \beta_4 y_t + error_t \tag{3}$$

Note that depending on cointegration rank all variables need not enter such a cointegration relation. With cointegration rank equal to one the relation would be as in (3). With cointegration rank higher than one at least on of the coefficients β_2 to β_4 must be zero. In any case we need to check whether λ_1 can be interpreted as equilibrium pass-through effect. In other words, we need to check whether, based on an estimate of the cointegration relation of the type (3), we can say that with a long-run change in e_t by 1 percent prices change by β_1 percent in equilibrium. This is a question about identification of the pass-through effect.

To establish the conditions for identification I invoke results of Johansen (2002). From the solution of the error-correction model it follows that the long-run value $X_{\infty/t}$ as a function of current values $(X_t, X_{t-1}, ..., X_{t-k+1})$ is given by

$$X_{\infty/t} = \lim_{h\to\infty} E\left(X_{t+h} \mid X_t, X_{t-1}, ..., X_{t-k+1}\right) = C\left(X_t - \sum_{i=1}^{k-1} \Gamma_i X_{t-i}\right) \tag{4}$$

where matrices C and Γ are defined as

$$C = \beta_{\perp} \left(\alpha'_{\perp} \Gamma \beta_{\perp}\right)^{-1} \alpha'_{\perp} \text{ and } \Gamma = I - \sum_{i=1}^{k-1} \Gamma_i$$

and $\alpha_{\perp}$ and $\beta_{\perp}$ are the orthogonal complements to α and β respectively. Thus, it follows from the definition of matrix C that the long-run changes in endogenous variables are proportional to $\beta_{\perp}$. A given long-run change $k \in sp\left(\beta_{\perp}\right)$ can be achieved either by adding k to all current values or by adding Γk to X_t- a short-run change. It is also assumed in what follows that cointegration vectors are identified using zero restriction, which justifies the interpretations used below (see Proposition 2 in Johansen, 2002). The following proposition gives a sufficient and necessary condition for identification of the pass-through effect.

Proposition 1. *Equilibrium pass-through effect is identified if and only if the cointegration rank r is equal to 1 plus the number of variables other than domestic prices with a non-zero coefficient in $k \in sp\left(\beta_{\perp}\right)$.*

Proof. X_t is a p_t dimensional vector of variables. Without loss of generality assume p_t is placed first and e_t second. Consider a the following vector of long-run changes: $k = \left(\lambda, 1, \mu, \mathbf{0}_{1x(p-2-n)}\right)$, that is, a long-run change in the nominal exchange rate by one unit accompanied by a long-run change in prices by λ units, while allowing for a non-zero effect on n variables in sub-vector μ. λ measures the equilibrium pass-through effect and is a parameter that needs to be uniquely identified. Note that $k \in sp\left(\beta_{\perp}\right)$, hence the parameters in k must solve $k'\beta = 0$. β is rxp and it must be identified using zero restriction (see Johansen, 2002). k has $n+1$ unknown parameters. $k'\beta = 0$ is therefore a system of r linear equations and $n+1$ unknowns. It has a unique solution when $r = 1 + n$. In such a case λ is uniquely identified. Unless we have some prior statistically non-testable information for parameters of μ this is also the only case when it can be identified from the estimated cointegration coefficients. ■

It directly follows from Proposition 1 that the identification of pass-through effect implies also that a long-run equilibrium change in the exchange rate rate has a non-zero equilibrium effect on $n = r - 1$ variables in X_t. This leads to the following corollary to Proposition 1.

Corollary 2. *When pass-through effect is identified in a p-dimensional system, permanent exchange rate changes are associated with a non-zero equilibrium changes in exactly $r - 1$ variables other than domestic prices p_t.*

Proposition 1 and its corollary have important economic implications since they imply that conditional on cointegration rank the equilibrium exchange rate pass-through on prices can be identified from cointegration coefficients, but permanent exchange rate changes are associated with different effects on the remaining variables of the system. For a better illustration of the identification issue let us consider the following example. In the system of variables (1) genuine cointegration is found for ranks 1 to 4. With rank 1 a single cointegrating relation can be conveniently written in regression format as (3) which corresponds to cointegrating vector $\beta = \left(1, -\beta_1, -\beta_2, -\beta_3, -\beta_4\right)'$. As discussed above we need to check whether β_1 can be interpreted as a measure of pass-through effect. Consider a long-run change $k = (\beta_1, 1, 0, 0, 0)'$, that is, a long-run change in prices by β_1 percent accompanied by a long-run change in the exchange rate by 1 percent, while leaving foreign prices, the interest rate spread and real output unchanged. Note that $k'\beta = 0$. In such a case $k \in sp\left(\beta_{\perp}\right)$ and we could interpret β_1 as the equilibrium pass-through effect that is consistent with a zero equilibrium effect on the remaining variables of the system.

If we want to consider an equilibrium change with a non-zero equilibrium effect on the remaining variables in the system and see if we can interpret β_1 as the pass-through effect we need to explore the feasibility of the long-run change of the form $k = (\lambda, 1, \mu, 0, 0)'$. Clearly such a vector is not orthogonal to β for any $\mu \neq 0$ and hence β_1 cannot be interpreted as the pass-through effect. In such a case the equilibrium pass-through effect cannot be directly obtained from estimated cointegration coefficients.

Next consider the case with $r = 2$. Without loss of generality assume that cointegrating vectors are identified in such a way that there is a $r \times r$ identity matrix as the upper block of β. In regression format they can be written as

$$\beta_1 = [1, 0, \beta_{13}, \beta_{14}, \beta_{15}]'$$
$$\beta_2 = [0, 1, \beta_{23}, \beta_{24}, \beta_{25}]'$$

In line with Proposition 1 in such a case the equilibrium exchange rate pass-through can be identified from cointegration coefficients if we allow for an accompanying non-zero effect on one additional variable. This implies that we need to consider long-run changes of the type $k = (\lambda, 1, \mu, 0, 0)'$ or $k = (\lambda, 1, 0, \mu, 0)'$ or $k = (\lambda, 1, 0, 0, \mu)'$, corresponding to non-zero long-run change in foreign prices, the interest rate spread and output respectively.

In either case, by solving $k'\beta = 0$ the equilibrium pass-through effect λ is identified and estimated by

$$\lambda = \frac{\beta_{1j}}{\beta_{2j}}; \quad j = 3, 4, 5.$$

With $j = 3$ we consider $k = (\lambda, 1, \mu, 0, 0)'$ - a long-run change in the exchange rate, domestic and foreign prices that is typically considered in the analysis of the purchasing power parity hypothesis. From an economic point of view such a change can be considered as a consequence of purely nominal factors (shocks). With $j = 4$ we consider $k = (\lambda, 1, 0, \mu, 0)'$ - a long-change the exchange rate, domestic prices and the interest rate spread. We can interpret such a change as coming from financial shocks and is associated by a different equilibrium exchange rate pass-through effect than in the case of a nominal shock. Finally, With $j = 5$ we consider $k = (\lambda, 1, 0, 0, \mu)'$ - a long-run change in the exchange rate, domestic prices and real output y, which comes about due to permanent real shocks with corresponding equilibrium exchange rate pass-through effect.

In the case of three cointegrating relations we would have

$$\beta_1 = [1, 0, 0, \beta_{14}, \beta_{15}]'$$
$$\beta_2 = [0, 1, 0, \beta_{24}, \beta_{25}]'$$
$$\beta_3 = [0, 0, 1, \beta_{34}, \beta_{35}]'$$

and the corresponding long-run changes, which according to Proposition 1 contain two variables in addition to the exchange rate and prices with non-zero coefficient. In particular, $k = (\lambda, 1, \mu_1, \mu_2, 0)'$ or $k = (\lambda, 1, 0, \mu_1, \mu_2)'$ or $k = (\lambda, 1, \mu_1, 0, \mu_2)'$. Also in such a case, the estimated equilibrium exchange rate pass-through can be obtained directly from the cointegration coefficients by solving $k'\beta = 0$ for these long-run changes.

The largest possible cointegration rank in our example is 4. In such a case there is only one unit root in the system and hence $\beta_\perp$ a one-dimensional space. Feasible long-run changes include non-zero effects on all modelled variables. The equilibrium exchange rate pass-through effect is in such as case the simplest to determine as the four cointegration relations include two variables each. If we identify the cointegration space such that one of the relations includes the exchange rate and domestic prices, the equilibirum exchange rate is measured directly by the corresponding cointegration coefficient.

These examples reveal that the identification of long-run or equilibrium pass-through effect depends on cointegration rank. Depending on rank we can find different possibilities of the long-run changes of other modelled variables other than the exchange rate and prices. Clearly, such long-run changes need to be sensible also from economic point of view, otherwise we reduce the issue of estimating the equilibrium pass-through effect to a mechanical procedure with limited value for policy makers.

When identification can be achieved we can also determine the corresponding contemporaneous pass-through effect – a short-run change – that supports a given long-run change leading to a conventional impulse response analysis that I also consider in the next section. As seen above, a given long-run change $k \in sp(\beta_\perp)$ can be achieved by adding Γk to X_t. We can interpret this change also as the effects of shocks that clearly have permanent effects on variables in X_t. In fact, this is a restriction on any type of shock in structural sense (real or nominal) that economic theory can justify to have a permanent change given by $k \in sp(\beta_\perp)$.

2.1. Implications of identification problem for other methodological approaches

The analysis thus far focused on the interpretation of cointegration coefficients and consequently highlighted potential weaknesses in existing studies using the cointegrated VAR framework to study the equilibrium or long-run exchange rate pass-through. However, the discussion of the identification problem has some implications also for single-equation and SVAR-based studies of pass-through effect.

It is clear from the above discussion that a given single-equation estimate of

$$p_t = \lambda_1(L)e_t = \lambda_2(L)p_t^* + \lambda_3(L)\left(i_t - i_t^*\right) + \lambda_3(L)y_t + \varepsilon_t$$

would not enable us to directly interpret λ_1 as the measure of pass-through effect. A ceteris paribus interpretation of λ_1 explicitly assumes that p_t^*, $i_t - i_t^*$ and y_t do not change as e_t changes, which is hard to assume from an economic point of view.

In general, any specification of the empirical model for estimation of the pass-through effect that contains variables that are according to economic theory in equilibrium dynamically linked to the nominal exchange rate calls for systems estimation of the model, and within that model checking for the identification of the equilibrium effect. This reasoning goes beyond the estimation of only exchange rate pass-through. As follows from Johansen (2002), it is applicable to any type of empirical analysis where correct interpretation of cointegration coefficients is of importance.

SVAR analysis of pass-through effect commonly relies on identification of exchange rate shocks and estimation of impulse responses to an exchange rate shock. As is shown in the next section also the approach used in this paper can accommodate impulse response analysis and study the short-run pass-through effects that lead to long-run changes. Note, however, that there is one important difference in the approaches. While the SVAR approach necessarily uses non-testable (just)identifying restrictions, the approach proposed in this paper does not rely on such restrictions and uses only the estimated cointegration coefficients. In this respect it is partial-identification scheme that does not need to impose a full set of identifying restriction on the VAR parameter to deliver the impulse response analysis of the exchange rate pass-through.

3. Empirical application - Exchange rate pass-through in the Euro area

This section illustrates the procedure of the identification of the exchange rate pass-through for the case of the Euro area. The system of variables I consider is the same as the one used in the example of the previous section:

$$X_t = \left(p_t, e_t, p_t^*, i_t - i_t^*, y_t\right), \tag{5}$$

where p_t stands for the log of the Euro area consumer price index excluding energy and food prices, e_t is the log of the nominal effective exchange rate, p_t^* is the log of the world GDP deflator, $i_t - i_t^*$ is the spread between the short-term interest rate in the Euro area and the US 3-month T-bills and y_t is the log of the Euro area GDP. The Euro area data come from the 2013 update of the Euro Area Wide Model dataset of Fagan et al. (2001). They are quarterly and cover the period 1990-2012.[3] The US data are taken from the FRED database.

The lag length of the system (2) has been chosen by complementary use of standard information criteria and the usual Wald-type tests for lag reduction. It proved sufficient to include two endogenous lags, which delivers also a statistically well specified model (see upper panel of Table 1). The test for cointegration rank in Table 1 indicates rank 2, which is consistent with the evidence of three large roots in the system.

[3]The data can be downloaded from the Euro area business cycle network webpage (www.eabcn.org/area-wide-model).

Table 1: Multivariate misspecification tests and characteristic roots and trace tests for the I(1) systems

Res. autocorr. 1	$F(25, 261) = 1.42$				p-val $= 0.09$	
Res. autocorr. 1-4	$F(100, 272) = 1.18$				p-val $= 0.15$	
Normality	$\chi^2(10) = 65.34$				p-val $= 0.00$	
	Modulus of 6 largest characteristic roots					
	0.99	0.93	0.93	0.89	0.89	0.55
Trace test	3.94	10.64	24.13	48.36	82.49	
p-value	0.05	0.34	0.20	0.04	0.00	
r	4	3	2	1	0	

Table 2: Estimated Cointegration Relations and Loading Coefficients

	β_1	β_2	α_1	α_2
p_t	1.00	-	-0.03	0.01
			(0.01)	(0.00)
e_t	-	1.00	0.11	0.01
			(0.29)	(0.02)
p_t^*	-1.18	-0.02	0.13	-0.01
	(0.17)	(2.11)	(0.05)	(0.00)
$i_t - i_t^*$	0.01	0.14	-20.15	0.84
	(0.00)	(0.03)	(5.17)	(0.45)
y_t	-0.17	-0.33	-0.07	-0.00
	(0.13)	(1.65)	(0.05)	(0.00)

Notes: Standard errors in parentheses.

The left panel of Table 1 presents the estimates of cointegration vectors. The right panel reports the corresponding adjustment coefficients. The cointegration coefficients are statistically identified by means of a leading identity matrix. Such an approach is convenient for the computation of the equilibrium exchange rate pass-through effect as demonstrated in the previous section.

Before proceeding to the discussion of how the equilibrium exchange rate pass-through can be estimated in the current empirical example it useful to consider an example that demonstrates potential pitfalls in interpreting cointegration coefficients. It can be shown in the present case that one cannot reject the hypothesis that the following cointegration vector lies in the cointegration space

$$\tilde{\beta} = [1, -1, -1, -0.13, 0.06]'$$

The likelihood ratio statistic of the test of the hypothesis that the second and the third element of this vector are equal to -1 is equal to 0.004 with corresponding p-value of 0.95. This implies that we cannot reject the hypothesis that one of the cointegration vectors can be written as

$$p_t = e_t + p_t^* + 0.13\,(i_t - i_t^*) - 0.06 y_t + error_t \tag{6}$$

Because the coefficients corresponding to the nominal exchange rate and the foreign price level are equal to one, a typical *ceteris paribus* interpretation of such a cointegration relation would be that the equilibrium exchange rate pass-through effect is perfect and, in addition, the purchasing power parity holds.

Note, however, that such an interpretation would be false. For the purchasing power parity to hold we need to consider a long-run change of the type $\tilde{k} = [1, 1, 1, 0, 0]$, i.e. domestic prices, foreign prices and the exchange rate moving one-to-one in the long run. But this is clearly not the case. It is evident that $\tilde{k}\tilde{\beta} = -1 \neq 0$, and hence neither the purchasing power parity nor the perfect pass-through assumptions hold.

From the estimates of cointegration coefficients in Table 2 we can estimate also the degrees of equilibrium exchange rate pass-through effect. Given that cointegration rank is set to two the discussion in Section 2 suggests that the equilibrium exchange rate pass-through is estimated as

$$\lambda = \frac{\beta_{1j}}{\beta_{2j}}; \quad j = 3, 4, 5.$$

conditional on whether we consider the accompanying long-run change in either foreign prices or the interest rate spread or the Euro area prices. In line with the discussion of the previous section we will label these changes as coming from nominal, financial and real permanent shocks respectively. It is worth remembering that these changes are required for identification of the equilibrium pass-through effect from the estimated cointegration coefficients reported in Table 2.

The estimates of the equilibrium pass-through effects are reported in Table 3. As we can observe they differ quite significantly depending on which variable other than domestic prices is allowed to change in equilibrium with the nominal exchange rate. To facilitate the interpretation of the differences in the pass-through effects Figures 1 - 3 report the corresponding impulse response functions that deliver the long-run changes and co-movements between prices and the exchange rate reported in Table 3.

The value of the equilibrium pass-through effect conditional on a nominal shock is surprising at first sight as it turns out to be highly negative. The results can be rationalized, however, by looking at the impulse responses in Figure 1 that are obtained by simulating the effect of an initial change in X_t by Γk.[4] We can observe that the nominal shock drives prices permanently down both in the Euro area and the rest of the world by practically the same amount. The adjustment is faster for the Euro area prices, which is consistent with a positive response of the interest rate spread. The corresponding change in the exchange rate is in principle allowed to be non-zero and from an initial negative response becomes only slightly and insignificantly positive. Given an almost parallel trajectory of prices, leaving the real exchange rate unchanged, weak adjustment through the nominal exchange rate is not surprising, and neither is an odd measure of equilibrium exchange rate pass-through effect.

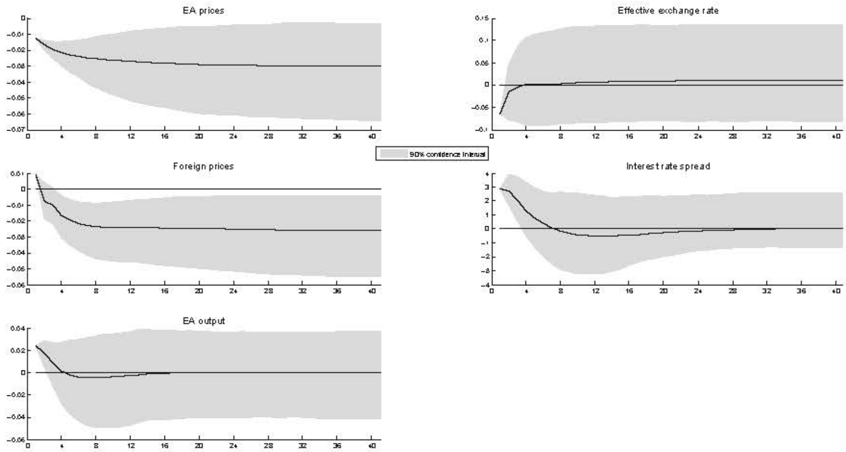
Table 3: Long-run changes and equilibrium exchange rate pas-through effect

Long-run shock	Equilibrium pass-through	Perfect pass-through test $\chi^2(1)$	p-val
Nominal	-2.99	$*$	
Financial	0.10	4.71	0.03
Real	0.35	0.58	0.44

$*$ no convergence in estimation algorithm

[4]The 90% confidence intervals are obtained by bootstrap.

Figure 1: Impulse responses to a permanent nominal shock



Conditional on a financial shock that permanently affects the interest rate spread the estimated equilibrium exchange rate pass-through is positive, but low. A 1 percent equilibrium increase in the effective exchange rate is associated with a 0.1 percent increase in the Euro area prices. Low equilibirum pass-through effect is confirmed by a formal test of perfect equilibrium pass-through, i.e. $\lambda = 1$. This would obtain if $\beta_{14} = \beta_{24}$, which is also the hypothesis tested by a likelihood ratio test. The test clearly rejects the perfect pass-through hypothesis.

The corresponding impulse responses in Figure 2 confirm the interpretation of long-run changes as coming from permanent financial shocks. The interest rate spread is permanently driven down, which immediately weakens the euro. Domestic prices quickly rise to the new long-run equilibrium, while output reacts only temporarily.

Finally, we turn to a real shock, a long-run change that permanently changes real GDP. In such a case the equilibrium pass-through effect is the highest, with the point estimated of 0.35. Moreover, a formal test cannot reject the hypothesis $\beta_{15} = \beta_{25}$, which implies a perfect equilibrium pass-through.

The impulse responses in Figure 3 show that in response to a permanent increase in the Euro area GDP that is accompanied by a permanent depreciation of the effective the exchange rate (induced by a temporary reduction in the interest rate spread) domestic prices gradually rise to the new equilibrium level. Relative to the case of the financial shock, the exchange rate pass-through is slower in the short-run but higher in the long run.

The interpretation requires of bit of caution as the estimated responses of the exchange rate and domestic prices results to be rather imprecisely estimated and consequently not statistically different from zero already at short horizons. This feature partially explains the results of the test for a perfect pass-through effect in Table 3.

Figure 2: Impulse responses to a permanent financial shock

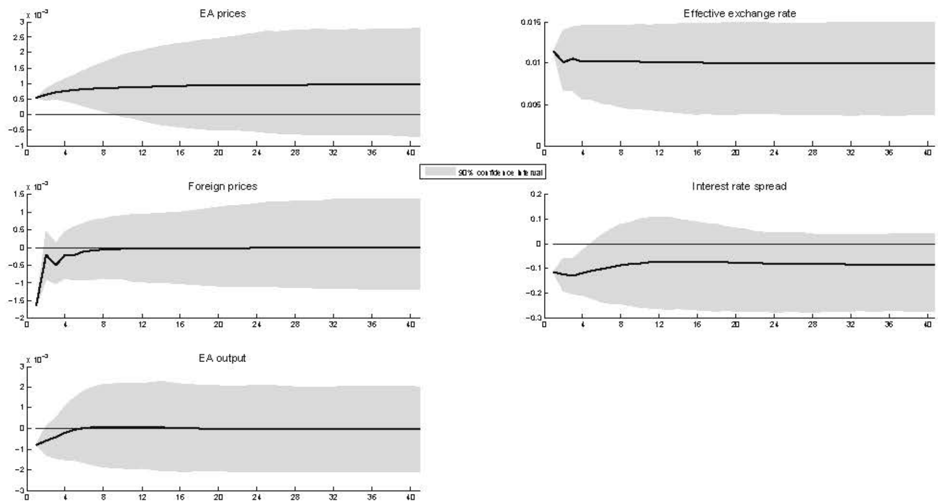
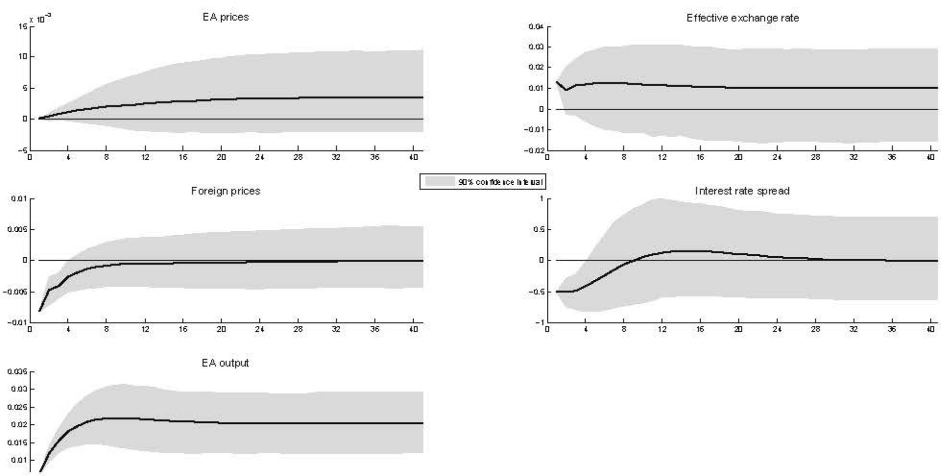


Figure 3: Impulse responses to a permanent real shock



4. Concluding discussion

The purpose of the paper is to contribute to the literature on exchange rate pass-through estimation from methodological and empirical point of view. The empirical analysis is performed within the cointegrated VAR framework that in principle enables the estimation of the equilibrium pass-through effect of nominal exchange rate changes on prices. As shown by Johansen (2002), this requires a proper interpretation of cointegration coefficients, which, combined with economic theory, in the present framework translates into the problem of identification of the equilibrium pass-through effect. Systems of variables for pass-through estimation must contain all crucial variables that account for complex macroeconomic interdependence in open economies. In such a case, we cannot discuss equilibrium effects of a one percentage point change in nominal exchange rate on prices without taking into account also the endogenous effect on other variables. This implies that identification cannot be automatically achieved for all orders of cointegration rank. Moreover, each possible value of cointegration rank leads to different conclusions about the equilibrium effects of exchange rate changes.

The process of identification of equilibrium pass-through is demonstrated on the Euro area data. It is shown that the equilibrium exchange rate pass-through is incomplete, but lower conditional on the permanent financial shocks and higher conditional on permanent increases in real output. For pure nominal price shock the pass-through effect may not even turn out to be positive.

These results offer a policy implication related to the expansive unconventional monetary policy measures introduced by the ECB in late 2014. These are expected to depreciate the euro relative to other major world currencies and consequently stimulate economic activities and curb deflationary pressures. From an economic point of view these unconventional policy measures are most closely related to the case of a permanent financial shock. The results in this paper show that the effects of a permanently weaker euro on economic activity is rather limited and it has a weak positive effect on the Euro area consumer prices.

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INNOVATION FOCUSED STRATEGY AND EARNINGS MANAGEMENT

NATHAN JEPPSON[1]
DAVID SALERNO [2]

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ABSTRACT: *This study utilizes three approaches to investigate the extent to which firms with an innovation focused strategy engage in earnings management through the use of income smoothing, real activities, and the use of discretionary accruals. Several results are reported. First, firms with an innovative strategy report a greater percentage of earnings in the fourth quarter indicating greater earnings management. Second, innovative firms use real activities to a greater extent than non-innovative firms to manage earnings when income approaches certain earnings benchmarks. Lastly, innovative strategy firms engage in the use of discretionary accruals to a greater degree than other firms.*

Keywords: *Earnings management; Innovation; Firm strategy; Earnings manipulation; Accruals*

JEL Classification: M41; L21; O32

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INTRODUCTION

The literature shows there are two basic types of business strategies: cost leadership and differentiation (Porter, 1985; Ittner & Larcker, 2001; Langfield-Smith, 1997). Firms adopting a cost leadership strategy focus on being the least expensive producer of a product or the least expensive provider of a particular service. On the other hand, firms pursuing a differentiation strategy attempt to offer a unique product or service. Often firms with a differentiation strategy, a growth strategy or an innovation strategy are referred to synonymously (Ittner & Larcker, 2001). In order to obtain their economic objectives, firms with a either a cost leadership or a differentiation strategy engage in innovative activities in several categories including extending their existing product range, increasing sales and market share, or cutting costs (Guan et al., 2009).

Innovation is widely considered to be the lifeblood of corporate survival and growth (Zahra & Covin, 1994). Ittner and Larcker (2001) define an innovative firm as one that focuses on being first-to-market with a variety of original products or services.[3] Most early empirical studies examining innovation are derived from the classic discussion provided

1 Montana State University, Bozeman, MT, USA, e-mail: nathan.jeppson@montana.edu

2 University of Scranton, Kania School of Management, Scranton, PA, USA, e-mail: david.salerno@scranton.edu

3 Ittner and Larcker (2001) indicate that innovative firms may also be referred to as "prospector" or "build" firms in the literature. Conversely, firms that follow a cost leadership strategy might also be termed "defender" or "harvest" firms.

by Schumpeter (1942). Schumpeter outlines that new technology is successful innovation through combined investment decisions. However firms that are regarded as innovative might be innovative in several different areas. For example, extant literature often classifies innovation into broad categories such as process innovation, product innovation, or business model innovation (e.g. Nicholas, 2008). While innovation is a complex construct, for purposes of this paper an innovative firm is one that pursues product innovations.

While it is clear that firms engage in earnings management, the motivation of this paper is to investigate the additional extent to which firms with strategy focused on innovation (IS firms) engage in earnings management. The existence of earnings management is well documented in the literature (e.g., Hayn 1995; Burgstahler & Dichev, 1997; Degeorge, Patel & Zeckhauser, 1999; Das, Shroff & Zhang 2009; see also literature regarding research and development intensive firms such as Cheng, 2004). Literature shows that earnings can be manipulated using either accounting accruals or real activities (e.g., reduction in research and development spending, see Cohen & Zarowin, 2010). Accrual-based earnings management has no direct effect on cash flows, while real activity-based earnings management will affect firm cash flows and could affect accruals as well.

Knowledge regarding the extent to which innovative firms participate in earnings manipulation will be of special interest to investors and to other stakeholders because an innovative strategy could provide several competitive advantages: developing new products or new product lines that enthuse the customer, keeping ahead of competitors in a given industry, and entering into new market segments or developing new businesses (Bowonder et al., 2010).

Extant research provides several indications that IS firms may be more likely to manage earnings than are non-IS firms. First, an IS firm's investment in new products, processes or business models is inherently risky and uncertain (Choi & Ahn, 2010), therefore, management may have more pressure from the market to smooth earnings in order to reduce these large aberrations in income. Second, IS firms may be in need of large pools of capital to support new research projects (Choi & Ahn, 2010). The need for capital may place pressure on management to inflate earnings in order to receive the desired funding from investors. IS firms invest more capital in research and development (R&D) than do non-IS firms and therefore face increased fundraising pressures. Third, recent research indicates that innovative firms are underpriced (Ciftci, Lev & Radhakrishnan, 2011) and that the market undervalues R&D expenditures (Ali, Ciftci & Cready, 2012) which could reasonably be expected to encourage firms to manage earnings. Finally, prior literature has clearly demonstrated that R&D expenses provide an opportunity for earnings management. R&D spending can easily be manipulated to influence earnings overall (Bartov, 1993; Bens, Nagar & Franco-Wong, 2002; Bens et al., 2003; Cohen, Dey & Lys, 2008). Also, seminal studies regarding earnings management by Hayn (1995) and Burgstahler and Dichev (1997) show that firms are more likely to manipulate earnings around zero values of net income. Since one method firms often use to manage earnings is through a reduction in R&D expenses (Baber, Fairfield & Haggard, 1991; Bushee, 1998; Cheng, 2004; Garcia & Young, 2009), IS firms might be more likely to manage earnings because they often have high levels of R&D that could be temporarily curtailed as a means of reducing expenses and thus managing earnings (Holthausen, Larcker & Sloan, 1995).

Three tests are used to examine the relationship between IS firms and earnings management. The first is a test of income smoothing following Murphy (2001). The firm's fourth quarter net income is regressed on a dummy variable representing high net income through the first three quarters of the current year, a proxy for innovation strategy, and an interaction term of those two variables. We find that IS firms derive a greater portion of their income from the fourth quarter of the year than non-IS firms indicating that IS firms are manipulating income to a greater extent. The second test investigates the use of real activities such as the strategic use of R&D spending discussed earlier in this section (Roychowdhury, 2006). We find that IS firms employ the use of real activities to meet earnings benchmarks to a greater degree than do non-IS firms, thus indicating a greater degree of earnings management. Finally, the third test examines earnings management by use of discretionary accrual techniques following Cohen, Dey, and Lys (2008). We find evidence that IS firms also use discretionary accruals to manipulate income more than non-IS firms. This study is distinct in that it examines the relationship between firm innovation focused strategy and earnings management. The results of this paper will contribute to the literature by revealing the impact that an overall innovative firm strategy has on earnings management.

The remainder of this study is organized as follows. Section 2 contains a discussion of the literature regarding strategy, innovation, and earnings management. Section 3 provides the hypotheses and research design. Results and discussion regarding the proposed tests are included in section 4. Section 5 provides a conclusion and limitations

1 RELATED PRIOR RESEARCH

According to Chaney et al. (1991), innovation is the basis for all economic growth and development. They outline three primary areas of innovation research: (1) the efficiency of innovation investment; (2) the Schumpeterian hypothesis; and (3) the social benefits of innovation.

First, the literature examines whether a competitive marketplace effectively and efficiently invests in new process, product, and business model development. For example, Matolcsy and Wyatt (2008) determine how technological innovations drive the market value of the firm through earnings growth. This study uses three factors to determine the level of innovation: the success of prior technology investments, the complexity of technology and the development period of the technology. The results show that when the three factors that facilitate innovation are present alongside earnings growth, the market value of equity is greatly enhanced. At the firm level, Inderst and Klein (2007) show how managers have a tendency to overinvest in their own projects during the corporate budgeting process due to their own biases.

Second, prior studies examine the "Schumpeterian hypothesis" and whether a monopoly (or near monopoly) is necessary to foster innovation (Boldrin & Levin, 2009). Smythe (2010) characterizes the Schumpeterian hypothesis as the idea that highly concentrated industries are more conducive to rapid technological innovation than less concentrated industries. For example, a study by Gayle (2003) conducts an empirical examination of the Schumpeterian hypothesis by using citation-weighted patent count to measure innovative output.

Finally, other research explores the role government has in fostering innovation and the social benefits of innovation. Social benefits of innovation are product inventions or process and business model developments that have value to society. For instance, innovations in the pharmaceutical industry have contributed to societal health while innovations in the high-tech industry have increased society's access to information. A recent example of this type of research is Wagner (2010) where the author explores the link between innovation with high social benefits and corporate social performance and the role that family firms play in this link. Wagner (2010) finds that family firms moderate the link between innovation and high social benefits and corporate social performance. We add to these three areas of innovation research by examining what effect the manipulation of earnings has on the expansion of innovative ideas.

The existence of earnings management is clearly demonstrated in the literature (e.g., Burgstahler & Dichev, 1997; Das, Shroff & Zhang, 2009; Degeorge, Patel & Zeckhauser, 1999; Hayn, 1995). Some limited empirical evidence also exists regarding the relationship between firms adopting innovation focused strategies and their likelihood to manage earnings. For example, Garcia and Young (2009) establish a link between managers curtailing R&D in response to target driven earnings pressures. Their study uses a large sample of R&D active United Kingdom firms.[4] The results suggest that these R&D active firms are more likely to manage earnings to meet certain earnings targets by limiting R&D expenses. Several other studies in the literature have also shown that managers reduce R&D spending to increase short-term performance (e.g., Cheng, 2004). Most recently Shust (2015) examines and finds that the extent to which firms engage in research and development or their R&D intensity level is positively associated with accrual-based earnings management. This paper extends these studies by examining whether IS firms use discretionary accruals and several other types of real activities (in addition to R&D expenses) to manage or smooth earnings.

Management is motivated to manage earnings for a variety of reasons. Graham et al. (2005) provides several reasons for earnings management to meet certain benchmarks. The dominant reason relates to stock price. Skinner and Sloan (2002), for example, document that there are severe negative price reactions when growth firms do not meet earnings expectations. Burgstahler and Dichev (1997) document that managers avoid reporting earnings decreases and losses to decrease costs imposed in transactions with shareholders. Based on prospect theory, managers may be highly motivated to avoid reporting a loss since the largest gains in utility occur when moving from an absolute loss to a gain (Burgstahler & Dichev, 1997). Major consequences for missing earnings targets are an increase in uncertainty about future prospects and the perception that missing

4 The criteria Garcia and Young (2009) use for R&D active firms are non-financial firms with at least three consecutive years of non-zero R&D expenditure over a 13 year period. Garcia and Young (2009) focus their tests exclusively on United Kingdom firms that expense all R&D as incurred.

targets may be a sign of previously unknown problems at the firm (Graham, Harvey & Rajgopal, 2005).

Despite its short term benefit, earnings management has future and long-term consequences. Earnings management using real activities, such as delaying R&D expenditures, could have a negative impact on future performance (Mizik, 2010). Degeorge et al. (1999) find that the future performance of firms suspect for boosting earnings across a threshold is poorer than other firms. Additionally, aggressive earnings management leading to accounting scandals results in harsh consequences such as a significant drop in the value of equity ownership, and severe penalties such as fines and sanctions imposed by the Securities and Exchange Commission, jail or probation time and job loss (Karpoff et al., 2008).

A common reason to manage earnings is to achieve a smoother earnings path. Earnings smoothing, or a reduction of variability in reported earnings, is preferred by investors (Barth et al., 1999) as evidenced by firms that smooth earnings being consistently priced at a premium (DeAngelo et al., 1996). In fact, analysts reward firms that engage in more aggressive earnings smoothing with higher Financial Analysts' Federation (FAF) disclosure scores (Shaw, 2003).

However, there are other reasons why firms smooth earnings. For example, managers at firms that have their bonuses based on internal standards will manage earnings to meet but not exceed budgeted performance thus achieving a smooth pattern of earnings (Murphy, 2001). Smoother earnings reduce the probability that firms will violate debt covenants because, as part of a smoothing strategy, firms will manipulate earnings to meet the thresholds outlined in the debt covenants (Blasco & Pelegrin, 2006). Smoother earnings lead to an improvement in initial public offerings, stock financed acquisitions and the overall financial conditions of many other operations as firms that that have shown to have a consistent pattern of earnings are priced and valued by investors at a premium (Blasco & Pelegrin, 2006).

Several studies indicate that firms willingly sacrifice value in order to improve reported earnings. Mizik (2010) assesses the aggregate financial consequences of cutting marketing as well as R&D spending to inflate earnings. Mizik (2010) contrasts the reduction of these discretionary expenses to inflate earnings or myopic management with accounting accruals-based earnings inflation and finds that myopia has a long-term net negative impact on firm value. Mizik (2010) also shows that myopic management, and not accrual-based manipulation, has the greater negative impact on future financial performance. Further, many top company executives concede that they are willing to reduce R&D and advertising expenses even if that reduction in expenses would lead to a reduction in value of the firm (Graham, Harvey & Rajgopal, 2005). Dechow and Sloan (1991) similarly find that when top executives are at the end of their tenure or when they are nearing retirement at a firm, their firms exhibit a reduction in R&D spending.

Other related studies include Das, Shroff and Zhang (2009) which investigates whether the pattern of quarterly earnings changes can provide an indication of earnings management. They find that reversals of year to date earnings patterns in the fourth quarter occur more frequently than should be expected if the earnings reversals occurred purely by chance. Several factors that were prevalent among firms with earnings reversals, including changes in R&D expenditures, were indicative of earnings management.[5] However, neither Das, Shroff and Zhang (2009) nor Mizik (2010) examine firms with an overall innovation strategy. Finally, previous research examines the relationship between R&D expenditures and meeting earnings forecasts and targets (Garcia & Young, 2009), while other research studies the impact that income smoothing has on earnings informativeness (Tucker & Zarowin, 2006).

2 RESEARCH DESIGN AND HYPOTHESES

Several studies in prior literature suggest that IS firms would be more likely to manage earnings than non-IS firms. First, Chaney, Devinney and Winer (1991) outline several areas from conception of a new innovation to the public release of that innovation where results from feasibility studies of new ideas, testing of new innovations, and sales of new products or ideas in the marketplace could influence earnings, analyst earnings forecasts, and other financial forecasts. Furthermore, profitability from innovative projects fluctuates widely due to the risky nature of taking new ideas through to completion as a successful product in the marketplace (see Marion & Friar, 2012). For example, Stevens and Burley (1997) estimate that, on average, for every 100 exploratory projects where R&D expense is incurred, only one successful product results.[6] Since an innovative firm's investment in new products and processes is inherently risky, management may have more pressure from the market to smooth earnings in order to reduce any aberrations in income as a result of R&D expenses from failed projects and profits from successful projects. Second, IS firms may be in need of large pools of capital to support new research projects. The need for such capital may place pressure on management to inflate earnings to meet analysts' expectations in order to receive the desired funding from investors (Fuller & Jensen, 2010). Because IS firms typically invest more capital in R&D and therefore face these fundraising pressures (Garcia & Young, 2009), it is reasonable to expect that earnings management might be used to attract capital to a greater degree than firms with low or no R&D programs. Third, research indicates that the market does not fully reward firms that engage in R&D. For example Ciftci, Lev and Radhakrishnan (2011) find that such firms are underpriced by the market. Moreover, consistent with the underpricing of such firms, Ali, Ciftci and Cready (2012) provide evidence that market participants undervalue R&D expenditures. Therefore it is reasonable to assume that firms that find themselves in this position would engage in earnings management to enhance their ability to attract capital. Finally, prior literature has clearly demonstrated that R&D expenses provide the opportunity for earnings management and have often been manipulated by management to influence overall earnings (Bartov, 1993; Bens, Nagar & Franco-Wong, 2002; Bens et al., 2003; Cohen, Dey & Lys, 2008).

5 Other factors Das, Shroff & Zhang (2009) find are prevalent among firms with earnings reversals include the size and direction of discretionary accruals, the reversal of subsequent accruals, the use of special items in the income statement, and the effective tax rate.

6 Stevens and Burley (1997) suggest that, on average, for every 3,000 raw ideas, there are 100 exploratory projects, 10 well-developed projects, 2 full-fledged product launches and 1 successful product.

We also consider the possibility, which enjoys very little support in the literature, that IS firms might be less likely to manage earnings. First, when IS firms are in a startup or growth phase they may place less emphasis on profitability than firms in the later phases of the corporate life cycle (Anderson & Zeithaml, 1984; Quinn & Cameron, 1983). Miller and Friesen (1984) explain that firms in the early stages of the life cycle are more innovative. Therefore, a firm in its early stages may be categorized as a IS firm when profitability is low and then later in the corporate life cycle when profitability is high may not be considered an IS firm. With this reduced emphasis on profitability, there would be less pressure to manage earnings during these early organizational phases. Since firms with a focus on innovation sometimes have negative earnings due to their startup nature, earnings management could be less prevalent among IS firms than among non-IS firms. Second, the motivation to manage earnings often stems from a need to raise capital. If an IS firm already has available sources of funding for future projects, either through venture capital or other profitable product lines, there would be less pressure to manage earnings (Graham, Harvey & Rajgopal, 2005).

Although the literature cited above offers two scenarios under which IS firms might be less likely to manage earnings, the current authors suggest that this evidence is weak. For example, the first reason cited is that firms in their early stage life cycle would be less likely to engage in earnings management because they would not be compelled to mask losses at that point because such losses would be expected by market participants. We acknowledge that this dynamic is possible; however there is no reason supported by the literature that would indicate that IS firms are any less likely to manage earnings in that environment than would be non-IS firms who are experiencing early life cycle losses. Therefore we find no reason to suspect that earnings management would be less likely in IS firms under those circumstances. The second reason cited above for less likely earnings management is that IS firms often obtain private venture capital to fund operations and thus have no need to raise capital through traditional public debt or equity sources. Therefore in the absence of such a need there would be no incentive to manage earnings. Although this scenario is likely true for some IS firms, there is no indication in the literature that IS firms have any less of a need for capital beyond private sources than do non-IS firms.

Because the reasons for expecting less earnings management among IS firms are not strongly supported by the literature, and because of the strong indications in prior literature cited above that suggest a positive relationship exists between IS firms and earnings management, we test the following hypotheses stated in the alternate form:

H1. Earnings smoothing is more prevalent among IS firms than among non-IS firms.

H2. Use of real activities to manipulate earnings is more prevalent among IS firms than among non-IS firms.

H3. Use of discretionary accruals to manipulate earnings is more prevalent among IS firms than among non-IS firms.

To test the hypotheses, three earnings management approaches are examined. The first approach (to test H1) is to investigate whether income smoothing exists. Prior research has examined income smoothing as evidence for earnings management (Matsuura, 2008; Shaw, 2003). Murphy (2001) examined the proportion of net income derived from the fourth quarter relative to the proportion of net income derived from the first three quarters of the fiscal year. Therefore, we test whether IS firms derive a greater (or smaller) proportion of income from the fourth quarter relative to non-IS firms.

The second approach (to test H2) is to test for the use of real activities by IS firms. One method that firms use to manage earnings through real activities is to reduce discretionary expenditures such as R&D expenses (Cardinal & Opler, 1995) and advertising and marketing expenses (Mizik, 2010). Roychowdhury (2006) develops empirical methods to detect real activity-based earnings management including cash flow from operations (CFO), production costs, and discretionary expenses. Roychowdhury (2006) argues that these variables capture the effect of real operations better than accruals. Then, these measures are used to detect real activities manipulation around the zero earnings and annual analyst forecasts thresholds. In a subsequent study (Cohen, Dey & Lys, 2008) also uses the Roychowdhury (2006) proxies for real-activity earnings management. Furthermore, other real activities that might be used to manipulate income include certain special items (Das, Shroff & Zhang, 2009) such as the delay of new product introductions and by offering certain customer incentives to boost product sales (Graham, Harvey & Rajgopal, 2005).[7]

Finally the use of discretionary accruals to manage earnings is examined (to test H3), which is the most commonly used measure to identify earnings management.[8] Burgstahler and Dichev (1997) document the existence of earnings management and indicate that besides using real activities, firms also use accruals to manage earnings. Discretionary accruals are normally identified using the modified "Jones Model" (Jones, 1991) as described in Dechow, Sloan and Sweeney (1995), Kothari, Leone and Wasley (2005), and Cohen, Dey and Lys (2008).[9] The original Jones Model estimates accruals as a function of a change in revenue and a change in property, plant and equipment. Then discretionary accruals are computed as the difference between the actual and predicted values of total assets. Since a higher than predicted level of discretionary accruals is an indicator that a firm might have engaged in earnings management, this equation computes discretionary accruals as the difference between the actual and the predicted value of total accruals.

7 Some special items could be used to manipulate income through accruals (i.e. write-downs of assets), some special items may be examples of real activity manipulation (i.e. non-recurring profit or loss on the sale of assets, investments, securities, among others) while others may be examples of either accrual or real activity manipulation (i.e. any significant nonrecurring items).

8 A recent study by Stubben (2010) finds that discretionary revenues can also be used to determine the level of earnings management a firm has engaged in. In fact, his study finds that revenue models are more likely than accrual models to indicate a combination of revenue and expense manipulation. Additionally, Dechow et al. (2012) develop a new approach for detecting earnings management that improves test power and specification. This new approach utilizes the information contained in the reversals of accruals to improve the power of testing for earnings by over 40%.

9 Dechow, Sloan, & Sweeney (1995) find the modified Jones Model to exhibit the most power in detecting earnings management.

2.1. Measurement of Innovation

Several previous papers use various approaches to measure innovation. Some commonly used proxies for innovation include R&D expenses (e.g., Cardinal & Opler, 1995; Ittner, Larcker & Rajan, 1997), number of patents (e.g., Francis & Smith, 1995; Holthausen, Larcker & Sloan, 1995), and new product releases (Cardinal & Opler, 1995; Ittner, Larcker & Rajan, 1997). Less commonly used proxies for innovation include the number of innovation-related press releases (Koku, 2010), revenue and income from acquisitions (Francis & Smith, 1995), and the ratio of capital expenditures to sales (Francis & Smith, 1995). Closely related measures of innovation include Ittner, Larcker and Rajan (1997) measures of firm growth and firm efficiency measured using market to book value and the number of employees to sales, respectively.

Following prior studies (e.g., Cardinal & Opler, 1995; Ittner, Larcker & Rajan, 1997), R&D expenses (Compustat XRD) are used to proxy for innovation. In order to operationalize R&D expenses as a proxy for innovation, the median value of R&D expenses scaled by total assets for each industry or 2-digit SIC code are computed. A dummy variable indicating high and low levels of R&D expenses for each firm-year is utilized. The variable indicates whether the firm's preceding three years average level of R&D spending is above or below the median value for each industry during the preceding three years.

2.2. Research Methodology

Three equations are used to test each of the approaches described in section 3.1. To test for income smoothing, the first equation is based on Murphy (2001) who identifies firms smoothing income in the fourth quarter. The following empirical equation is employed:

$$\begin{aligned} Qtr4_{it} = \beta_1 + \beta_2 YTDDIFF_{it} + \beta_3 INNOV_{it} + \beta_4 YTDDIFF_{it} * INNOV_{it} + \beta_5 AGE_{it} + \beta_6 MTB_{it} + \\ \beta_7 MKTVAL_{it} + \beta_n Industry + \varepsilon_{it} \end{aligned} \quad (1)$$

where, for each firm *i* and year *t*:

Qtr4 is the percent of annual net income (Compustat NI) derived from the fourth quarter;

YTDDIFF is the difference in net income (Compustat NI) through the first three quarters in year t with the net income through the first three quarters in year t-1;

INNOV is a dummy variable equal to one if the three year mean of R&D spending in years *t-3*, *t-2*, and *t-1* (Compustat XRD) scaled by total assets (Compustat AT) is above the industry median in years *t-3*, *t-2*, and *t-1*; otherwise, it is equal to zero;

AGE is the number of years since the initial public offering of the firm;

MTB is the market value of the firm (Compustat MKVALT) divided by the book value of the firm (Compustat CEQ);

MKTVAL is the market value of equity (Compustat MKVALM); and *Industry* represent dummy variables to indicate two-digit SIC code categories.

This equation examines whether firms with innovation focused strategies smooth earnings by artificially inflating or reducing the fourth quarter income once the income through the first three quarters of the year is known. Absent of earnings management and seasonal fluctuations in business activity, the dependent variable, *Qtr4*, would approximate one-quarter of a firm's annual net income because *Qtr4* is the percent of annual net income (Compustat NI) derived from the fourth quarter. Prior literature has shown that due to income smoothing, higher income through the first three quarters of the current year compared to income during the same period in the prior year has a downward effect on the fourth quarter's earnings as firms exceeding their targets in the first three quarters may adjust their fourth-quarter accruals downward to "save" for the future (Das, Shroff & Zhang, 2009; Murphy, 2001). For firm with net income, this would result in a negative coefficient on the *YTDDIFF* variable. Furthermore, because of the larger pool of marketing and R&D expenses in IS firms, the expectation of this study is that those firms will be more likely to smooth earnings than non-IS firms (Das, Shroff & Zhang, 2009; Mizik, 2010). For observations with annual net income, the coefficient on the interaction term *YTDDIFF*INNOV* is also expected to be negative. Such a result would indicate that IS firms smooth earnings by decreasing earnings to a greater extent during the fourth quarter. Conversely, for firms with annual net loss, the coefficient on both the YTDDIFF and the interaction would be expected to be positive. This result for firms with a net loss would indicate that they smooth their losses by increasing losses in the fourth quarter when their losses through the first three quarters of the current year are smaller than that of the same period in the prior year.

The second equation tests management's use of real activities. Under this method, following Cohen, Dey and Lys (2008), three tests for abnormal activities are performed: abnormal cash flow from operations; abnormal production costs; and abnormal discretionary expenses. Discretionary expenses are defined as the sum of advertising expenses, R&D expenses, and selling, general and administrative (SG&A) expenses. Each model measures the deviation from the predicted value in the corresponding industry-year regression. Although capitalization of development costs could have an impact on real activities earnings management and thus increase the deviation from predicted values in equation (4) below, because the firms in our sample generally use U.S. GAAP which precludes capitalization of such costs with narrow exceptions for software and website development costs, we expect any impact to be diminutive. Therefore following Cohen, Dey & Lys (2008) the normal levels of cash flow from operations, production costs, and discretionary expenses are generated by first estimating normal cash flow from operations *(CFO)* as follows:

$$CFO_{it} = \beta_1 \left({}^{1}/_{Assets_{it-1}} \right) + \beta_2 MV_{it} + \beta_3 Q_{it} + \beta_4 Sales_{it} + \beta_5 \Delta Sales_{it} + \varepsilon_{it} \quad (2)$$

The normal level of production costs *(Prod)* are estimated as:

$$Prod_{it} = \beta_1 \left({}^{1}/_{Assets_{it-1}} \right) + \beta_2 MV_{it} + \beta_3 Q_{it} + \beta_4 Sales_{it} + \beta_5 \Delta Sales_{it} + \beta_6 \Delta Sales_{i,t-1} + \varepsilon_{it} \quad (3)$$

Next, the normal level of discretionary expenses (*DiscExp*) is modeled as:

$$DiscExp_{it} = \beta_1 \left({}^{1}/_{Assets_{it-1}} \right) + \beta_2 MV_{it} + \beta_3 Q_{it} + \beta_4 INT_{it} + \beta_5 Sales_{i,t-1} + \varepsilon_{it} \tag{4}$$

In these equations, *CFO* (Compustat OANCF – XIDOC) is as reported in the statement of cash flows, scaled by total assets (Compustat AT); *MV* is the natural log of market value (Compustat PRCCM * CSHO); *Q* is Tobin's Q (Compustat (PRCCM * CSHO) + PSTK + DT + DLC) scaled by total assets; *Sales* is net sales (Compustat SALE) scaled by total assets; *Prod* represents the production costs, defined as the sum of Cost of Goods Sold (Compustat COGS) and change in inventory (Compustat INVT) scaled by total assets; *DiscExp* represents the discretionary expenditures, defined as the sum of advertising expenses (Compustat XAD), R&D expenses (Compustat XRD), and selling, general and administrative expenses (Compustat XSGA) scaled by total assets, and *INT* is internal funds (Compustat IB + XRD + DP). Abnormal *CFO*, abnormal production costs, and abnormal discretionary expenses are computed as the difference between the actual values and the normal levels predicted from equations (2), (3), and (4). These three variables are then used as proxies for real activity earnings management in the following equation:

$$\begin{aligned} Abnormal\ Activity = {} & \beta_0 + \beta_1 INNOV_{it} + \beta_2 Bench_{it} + \beta_3 INNOV_{it} * Bench_{it} + \beta_4 Big_{it} + \\ & \beta_5 \Delta GDP_t + \beta_6 AGE_{it} + \beta_7 MTB_{it} + \beta_n Industry_i + \beta_n Year_t + \varepsilon_i \end{aligned} \tag{5}$$

where for each firm *i* and year *t*:

Abnormal Activity is one of three measures of abnormal activity: abnormal cash flow from operations, abnormal production costs; or abnormal discretionary expenses;

Bench is an indicator variable that is set equal to one if (a) net income divided by total assets is between 0 and 0.01, or (b) the change in net income divided by total assets between *t – 1* and *t* is between 0 and 0.01, zero otherwise;

Big is a dummy variable equal to 1 if the auditor is a Big 4 audit firm;

ΔGDP is the change in gross domestic product (Compustat GDP);

Industry represent dummy variables to indicate two-digit SIC code categories; and

Year is dummy variables to control for year effects.

All other variables are defined as in prior equations.

As in Gunny (2010), we include the indicator variable, *Bench*, which identifies firms that have just met one or both of two earnings benchmarks. These two benchmarks are earnings that are just above zero or earnings that are just above the prior year's earnings. We also interact this indicator variable for earnings benchmarks with the test variable for innovation. A significant result on the interaction term would indicate IS firms engage in incrementally different earnings management behavior.

For given sales levels, firms that manage earnings upward are likely to have unusually high or low cash flow from operations, unusually low discretionary expenses, or unusually high production costs. Either unusually high or low cash flow from operations could indicate earnings management. Unusually high cash flow may result from the reduction of cash expenses. Unusually low cash flow from operations could result from the acceleration of sales through price discounts or lenient credit terms (Cohen, Dey and Lys 2008). Therefore the expectation is that the coefficient of *INNOV* and the interaction between *INNOV* and *Bench* in Equation (5) will be either positive or negative for abnormal cash flow, negative for abnormal discretionary expense and positive for abnormal production costs. Such a result would indicate that innovative firms manage earnings by manipulating these real activities more than other firms in periods when a change in these income statement items will increase the likelihood of receiving favorable terms of financing or to meet analysts' earnings targets.

The third equation is used to test the extent to which IS firms engage in earnings management by using discretionary accruals. As suggested by Cohen, Dey, and Lys (2008), the equation is developed by starting with the Jones Model (Equation 6) for determining discretionary accruals. Discretionary accruals are computed as the difference between the actual and predicted values of total accruals as follows:

$$TA_{it} = \beta_0 + \beta_1 \left({}^{1}/_{Assets_{it-1}} \right) + \beta_2 \Delta Sales_{it} + \beta_3 PPE_{it} + \varepsilon_{it} \qquad (6)$$

where for each firm *i* and year *t*:

TA is total accruals scaled by lagged total assets (Compustat AT) where total accruals is earnings before extraordinary items and discontinued operations (Compustat IBC) less cash flows from operations (Compustat OANCF - Compustat XIDOC);

ΔSales is change in sales (Compustat SALE) scaled by lagged total assets; and

PPE is net property, plant, and equipment (Compustat PPEGT) scaled by lagged total assets.

Then, following Cohen, Dey, and Lys (2008) the coefficient estimates obtained in Equation (6) are used to estimate the firm-specific normal accruals (NA_{it}) for the sample firms:

$$NA_{it} = \beta_0 + \beta_1 \left({}^{1}/_{Assets_{it-1}} \right) + \beta_2 (\Delta Sales_{it} - \Delta AR_{it}) + \beta_3 PPE_{it} \qquad (7)$$

where for each firm *i* and year *t*:

NA is normal accruals; and

ΔAR is change in accounts receivable (Compustat RECT) scaled by lagged total assets.

All other variables are defined as in prior equations.

The discretionary accruals variable (DA) is computed as the difference between TA and NA and is used as the dependent variable in the following equation:

$$Accruals = \beta_0 + \beta_1 INNOV_{it} + \beta_2 Bench_{it} + \beta_3 INNOV_{it} * Bench_{it} + \beta_4 Big_{it} + \beta_5 \Delta GDP_t + \beta_6 MKTVAL_{it} + \beta_7 AGE_{it} + \beta_8 MTB_{it} + \beta_n Industry_i + \beta_n Year_t + \varepsilon_i \quad (8)$$

where for each firm i and year t:

Accruals is defined as one of three measures of discretionary accruals (DA): (1) the absolute value of discretionary accruals, (2) positive discretionary accruals, or (3) negative discretionary accruals.

All other variables are defined as in prior equations.

It is anticipated that the coefficient on the interaction *INNOV*Bench* in Equation (8) will be significant. Such a result for each of the three measures of discretionary accruals would suggest that accrual based earnings management is more prevalent among IS firms than among non-IS firms.

3 EMPIRICAL RESULTS

Table 1 summarizes the two samples used in this study: a smoothing sample, and an earnings management sample.

Table 1 - Innovation Strategy Sample Selection Procedures

Selection Procedure	*Smoothing Data*	*Earnings Management Data*
Total number of firm year observations in Compustat	20,055	19,791
Less: Non-innovative industries	---	8,506
Less: Extreme fourth-quarter income[a]	(4,006)	---
Final sample	16,049[b]	11,285

[a] Consistent with prior literature, observations are eliminated that contain fourth-quarter income shares less than zero or exceeding unity.

[b] In Tables 2 & 3, for ease of interpretation this final sample is split into two groups, observations with annual net income and annual net loss, with sample sizes of 7,750 and 8,299, respectively.

Each of the two data samples initially includes all available Compustat observations from 1991 to 2010. For the smoothing data set, we begin with all available observations. First, we eliminate observations with missing variables. Then, following Murphy (2001), firms with fourth quarter net losses or firms where fourth quarter income exceeds unity are eliminated. This results in a final sample size of 16,049.[10] For the earnings management sample, we begin with all available observations. Then, in order to focus our tests on

10 The smoothing data sample is not reduced to these eight industries in order to preserve a reasonable final sample size. Therefore, all industries are included in the smoothing data sample.

industries where innovation plays a key role in management strategy, we eliminate firms that are not in innovative industries (e.g., Collins, Maydew, & Weiss, 1997; Dechow & Sloan, 1991; Francis & Schipper, 1999; Lev & Sougiannis, 1996). Innovative industries are defined following Cao and Laksmana (2010) as either R&D intensive, intangible-intensive, or high-tech.[11] This results in the inclusion of firms from 137 different four-digit SIC coded industries in our earnings management sample. These procedures result in a final sample size of 11,285 for the earnings management data set.

3.1 Smoothing Data Results

Table 2 presents the descriptive statistics and correlations for each of the variables used in the smoothing data tests. Panels A and B present descriptive statistics and correlations for observations with annual net income, while Panels C and D present descriptive statistics and correlations for observations with annual net loss. In order to differentiate between their distinct set of incentives, we split the smoothing sample into two subsamples. The first includes firms with annual net income and the second includes firms with annual net loss. Firms with annual net income are motivated to smooth their annual net income by reducing fourth quarter income when income through the first three quarters of the current year exceeds income through the same period in the prior year (Murphy, 2001). This results in the percentage share of net income being smaller for firms with net income that engage in earnings smoothing. Therefore the coefficient on the *YTDDIFF* variable and the interaction term for firm with net income that smooth earnings would be expected to be negative. Firms with annual net losses are less motivated to smooth income due to less emphasis on profitability (Anderson & Zeithaml, 1984). Still, if firms with annual net losses do engage in earnings management, their fourth quarter loss will make up a larger portion of annual net loss. Therefore the coefficient on the *YTDDIFF* variable and the interaction term for firm with net loss that smooth earnings would be expected to be positive.[12]

In Panel A of Table 2, the dependent variable, *Qtr4*, has a mean (median) value of 0.327 (0.290) and a standard deviation of 0.181. If earnings were distributed evenly across the four quarters of the year, the expected value of *Qtr4* would be 0.25. Therefore, on average,

11 These industries and corresponding two-digit SIC codes are: (1) chemical and allied products - 28; (2) machinery - 35; (3) electric and electric supplies - 36; (4) transportation equipment - 37; (5) measuring and photographic goods - 38; (6) communications - 48; (7) business service - 73; and (8) engineering, accounting and related service - 87. Cao and Laksmana (2010) note that each of these industries were identified as R&D intensive, intangible-intensive or high-tech industries by Collins, Maydew and Weiss (1997), Dechow and Sloan (1991), Francis and Schipper (1999), and Lev and Sougiannis (1996).

12 This may best be explained by using a numerical example. If during the prior year, a given firm experiences a loss of $750 through the first three quarters and then has losses in the fourth quarter of $250, the annual loss would be $1,000, with the fourth quarter comprising 25% of the annual loss. Then, if during the first three quarters of the current year, the firm experiences a loss of only $650, the value of the loss in the current year is smaller than the same period of the prior year. Then, in order to match the prior year annual loss of $1,000, the firm may have losses of $350, or 35% of the annual loss. Therefore, as described, firms with annual net losses that have a smaller loss through the first three quarters of the year compared to the prior year's first three quarters, will have a fourth quarter loss that makes up a larger portion of the current year's loss when the firm is smoothing earnings.

the observations in the sample have 31% higher earnings than would be expected if earnings were distributed evenly throughout the fiscal year.

Similarly, the variable, *YTDDIFF*, has a mean (median) value of 25.76 (3.011) and a standard deviation of 653.1. If earnings were consistent from one year to the next (no growth in earnings from the prior year), the expected value of *YTDDIFF* would be zero, indicating that it is equally likely that earnings through the first three quarters of the year would be higher or lower than the first three quarters of the previous year.

In Panel B of Table 2, both the *AGE* variable and *MTB* variable have significant Spearman correlations (Pearson only *AGE* variable correlation is significant) to the *INNOV* test variable. The Spearman (Pearson) correlation between the test variable *INNOV* and the control variables *AGE* is negative at -0.075 (-0.064) while the test variable's correlation with *MTB* is positive at 0.129 (0.008).

The descriptive statistics and correlations for observations with annual net loss as shown in Panels C and D of Table 2 are similar to those with annual net income with only a few exceptions. The mean (median) value for *YTDDIFF* is negative at -22.05 (-0.978) indicating that loss firms typically perform better in the first three quarters of the prior period than the current period. Also, the mean (median) value for *INNOV* is much higher at 0.400 (0.000) indicating that there are more innovative firms on average that have a net loss for the period. In untabulated results regarding the smoothing sample, we find that the average age of IS firms is 15.1 years, while the average age of non-IS firms is 16.2 years. Therefore, on average, an IS firm is on average 7% younger than non-IS firms in the smoothing sample.

Table 3 presents the results of our tests of income smoothing regarding fourth-quarter shares of net income on year-to-date income (relative to the prior year) including interactions for innovative firm strategy. Panel A presents results for observations with annual net income while Panel B presents results for observations with annual net loss. The first column of Panel A in Table 3 presents the regression results of Equation (1) excluding the control variables for industry, age, and growth while the second column presents the regression results for the entire equation. In both cases, the coefficients for *YTDDIFF* are negative and significant indicating that firms smooth annual net income by decreasing reported earnings in the fourth quarter of their fiscal year if earnings through the first three quarters of the fiscal year exceed earnings through the same period of the prior year. This result for the variable *YTDDIFF* is consistent with Murphy (2001). In both regressions, the coefficients for *INNOV* are positive and significant, indicating that IS firms have higher earnings during the fourth quarter of their fiscal year when compared to non-IS firms. This indicates that IS firms report a greater percentage of their income during the fourth quarter of the year than do other firms, providing evidence for H1. Therefore, IS firms smooth their income to a greater extent than other firms by manipulating their fourth quarter income upward. The coefficient for the *INNOV* variable suggests that IS firms report 4.2% more income than other firms, for a total of 39.2% of their annual income, during the fourth quarter of the year. Furthermore, the coefficients of the interactive variable of *YTDDIFF* and *INNOV* are negative and significant, suggesting that smoothing does occur to a greater extent during years where their income is higher though the first three quarters of the year.

The first column of Panel B in Table 3 presents the regression results of Equation (1) excluding the control variables for industry, age, and growth while the second column presents the regression results for the entire equation. In each regression, the coefficients for *YTDDIFF* are significant, suggesting that loss firms do report a significantly different portion of their loss during the fourth quarter when the current year's loss is through the first three quarters of the year is smaller than that of the first three quarters in the prior period. Similarly, in both regressions, the coefficients for *INNOV* are negative and significant indicating that IS firms that have an annual net loss experience a fourth quarter that makes up a smaller share of their annual net loss than that of non-IS firms. This result supports H1 and indicates that IS firms are managing their income more than non-IS firms by reporting smaller losses during the fourth quarter of the year, thus decreasing their annual loss. However, the coefficient on the interaction variable *YTDDIFF*INNOV* is not significant. [13]

Table 2 Descriptive statistics for smoothing data set for the period from 1994-2010

Panel A: Descriptive statistics for observations with annual net income (Sample size is 7,750)

Variable	Mean	Median	Standard deviation	25th Percentile	75th Percentile
Qtr4	0.327	0.290	0.181	0.224	0.391
YTDDIFF	25.76	3.011	653.1	-0.333	14.23
INNOV	0.105	0.000	0.307	0.000	0.000
AGE	16.63	16.00	4.931	14.00	19.00
MTB	4.344	2.454	79.03	1.505	4.045
MKTVAL	2,532	563.4	11,060	145.6	1667

Panel B: Spearman/Pearson correlations for observations with annual net income

Variable	*Qtr4*	*YTDDIFF*	*INNOV*	*AGE*	*MTB*	*MKTVAL*
Qtr4	---	-0.018	**0.059**	**-0.042**	0.001	**-0.026**
YTDDIFF	**-0.095**	---	-0.005	0.010	0.000	**0.155**
INNOV	**0.055**	**0.024**	---	**-0.064**	0.008	-0.001
AGE	**-0.053**	**-0.020**	**-0.075**	---	0.006	**0.054**
MTB	**0.120**	**0.204**	**0.129**	**-0.033**	---	0.011
MKTVAL	**-0.030**	**0.340**	**-0.113**	**0.022**	**0.420**	---

Spearman is on the bottom left, Pearson is on top right. Bold text indicates significance at the 0.1 level or better.

13 In untabulated results, when controlling for the previous year's fourth quarter percent of annual net income (Compustat NI), results are unchanged.

Table 2 (continued)

Panel C: Descriptive statistics for observations with annual net loss (Sample size is 8,299)

Variable	Mean	Median	Standard deviation	25th Percentile	75th Percentile
Qtr4	0.334	0.279	0.212	0.196	0.422
YTDDIFF	-22.05	-0.978	890.3	-7.876	1.586
INNOV	0.400	0.000	0.490	0.000	1.000
AGE	15.28	15.00	4.592	12.00	18.00
MTB	4.803	1.805	112.3	0.622	4.546
MKTVAL	348.0	63.93	2,492	16.03	209.4

Panel D: Spearman/Pearson correlations for observations with annual net loss

Variable	*Qtr4*	*YTDDIFF*	*INNOV*	*AGE*	*MTB*	*MKTVAL*
Qtr4	---	0.008	**-0.129**	**0.078**	-0.010	0.012
YTDDIFF	**0.039**	---	0.004	-0.009	0.001	**-0.261**
INNOV	**-0.102**	**0.118**	---	**-0.062**	-0.008	**-0.033**
AGE	**0.099**	**-0.022**	**-0.076**	---	-0.007	0.010
MTB	**-0.053**	**0.023**	**0.104**	**-0.035**	---	0.010
MKTVAL	-0.018	**-0.230**	**-0.064**	**-0.157**	**0.380**	---

Spearman is on the bottom left, Pearson is on top right. Bold text indicates significance at the 0.1 level or better.

Table 3 Coefficients of OLS regressions of fourth-quarter share of net income on year-to-date income (relative to prior year), with interactions for innovative firm strategy from 1994 to 2010.

Panel A: Observations with annual net income

	Dependent variable: *Qtr4*	
Independent variables[a]	Coefficient (t-statistic)	Coefficient (t-statistic)
Intercept	0.327 (148.4)***	0.377 (61.76)***
YTDDIFF[b]	-0.263 (-9.02)***	-0.256 (-7.15)***
INNOV	0.046 (5.07)***	0.045 (4.80)***
*YTDDIFF * INNOV*	-0.001 (-2.79)***	-0.001 (-2.79)***
AGE		-0.001 (-2.95)***
MTB		0.003 (4.67)***
MKTVAL		-0.000 (-0.93)
Industry Controls		Included
# of observations	7,750	7,750
Adjusted R^2	0.013	0.032

***, **, * Indicates significance at the 1 percent, 5 percent and 10 percent levels, respectively.

[a]Continuous variables have been winsorized at the 1% and 99% levels to ensure results are not sensitive to extreme observations.

[b]Values for this variable have been multiplied by one thousand for ease of interpretation.

Table 3 (continued)

Panel B: Observations with annual net loss

	Dependent variable: *Qtr4*	
Independent variables[a]	Coefficient (t-statistic)	Coefficient (t-statistic)
Intercept	0.361 (108.8)***	0.409 (59.90)***
YTDDIFF[b]	0.286 (7.18)***	0.351 (8.37)***
INNOV	-0.060 (-13.18)***	-0.050 (-11.12)***
*YTDDIFF * INNOV*[b]	-0.236 (-1.06)	0.279 (-1.26)
AGE		0.004 (6.68)***
MTB		-0.001 (-3.57)***
MKTVAL[b]		0.007 (4.02)***
Industry Controls		Included
# of observations	8,299	8,299
Adjusted R^2	0.023	0.046

***, **, * Indicates significance at the 1 percent, 5 percent and 10 percent levels, respectively.

[a]Continuous variables have been winsorized at the 1% and 99% levels to ensure results are not sensitive to extreme observations.

Table 4 Descriptive statistics for earnings management data set for the period from 1994-2010

Panel A: Descriptive statistics (Sample size is 11,285)

Variable	Mean	Median	Standard deviation	25th Percentile	75th Percentile
AbCFO	0.001	0.068	2.774	-0.176	0.260
AbPROD	-0.126	-0.099	2.429	-0.248	0.064
AbDISCEXP	-0.265	-0.251	7.149	-0.469	0.019
ABSDA	1.007	0.104	14.84	0.044	0.244
DA	-0.053	0.027	14.87	-0.070	0.133
INNOV	0.226	0.000	0.418	0.000	0.000
Bench	0.468	0.000	0.499	0.000	1.000
Big	0.735	1.000	0.441	0.000	1.000
ChgGDP	240.5	312.0	255.6	167.9	375.0
MKTVAL	2,830	247.4	12,879	46.10	1,107
AGE	15.62	15.00	5.448	12.00	31.00
MTB	2.853	2.137	67.28	1.137	3.928

Table 4 (continued)

Panel B: Spearman/Pearson correlations[a]

Variable	(A)[b]	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
(A)	---	**-0.325**	**-0.665**	**0.050**	**-0.025**	**-0.061**	**0.048**	**0.051**	**0.017**	**0.037**	-0.013	0.003
(B)	**-0.292**	---	**0.620**	**-0.133**	**0.017**	**-0.022**	**0.025**	**0.023**	**0.020**	-0.007	**0.027**	-0.001
(C)	**-0.291**	**-0.410**	---	**-0.048**	**-0.041**	**0.057**	**-0.018**	0.006	**-0.017**	-0.000	0.002	-0.001
(D)	**-0.151**	**-0.047**	**0.130**	---	**-0.070**	0.000	**-0.022**	**-0.052**	-0.006	-0.010	**-0.022**	-0.011
(E)	**-0.052**	**-0.028**	**-0.035**	**0.177**	---	0.013	-0.004	-0.009	**-0.029**	0.000	0.012	0.011
(F)	**-0.217**	**-0.184**	**0.470**	**0.112**	-0.014	---	**-0.229**	**-0.062**	**0.017**	**-0.065**	**-0.043**	0.010
(G)	**0.356**	0.010	**-0.403**	**-0.147**	**0.131**	**-0.229**	---	**0.181**	**0.054**	**0.094**	**0.072**	-0.002
(H)	**0.348**	**-0.063**	**-0.175**	**-0.189**	**-0.073**	**-0.062**	**0.181**	---	**0.042**	**0.118**	**-0.040**	0.011
(I)	**0.031**	**0.061**	**-0.047**	**0.033**	0.005	**0.024**	**0.063**	**0.053**	---	**0.020**	**0.155**	-0.001
(J)	**0.726**	**-0.169**	**-0.384**	**-0.194**	**-0.052**	**-0.208**	**0.369**	**0.514**	**0.029**	---	**0.090**	0.010
(K)	**-0.091**	**0.137**	**-0.100**	**-0.049**	-0.028	**-0.046**	**0.072**	**-0.053**	**0.196**	**-0.016**	---	-0.009
(L)	**0.276**	**-0.203**	0.011	0.009	**0.033**	**0.081**	**0.107**	**0.139**	**-0.193**	**0.398**	0.012	---

[a]Spearman is on the bottom left, Pearson is on top right. Bold text indicates significance at the 0.1 level or better.

[b]Column and row headings:

(A) *AbCFO*

(B) *AbPROD*

(C) *AbDISCEXP*

(D) *ABSDA*

(E) *DA*

(F) *INNOV*

(G) *Bench*

(H) *Big*

(I) *ChgGDP*

(J) *MKTVAL*

(K) *AGE*

(L) *MTB*

3.2 Earnings Management (Real Activities and Discretionary Accruals)

Table 4 presents the descriptive statistics and correlations for each of the variables used in the earnings management sample for tests regarding both accrual based earnings management and real activity management. Panel A of Table 4, which provides descriptive statistics, shows that while the mean (median) value for *DA* (the difference between total accruals and fitted normal accruals) is near zero at -0.053 (0.027), the mean (median) value for *ABSDA* (the absolute value of the difference between total accruals and fitted normal accruals) is 1.007 (0.104). Since the *ABSDA* variable captures the discretionary accruals regardless of the direction of the accrual, the magnitude of the mean value of *ABSDA* is far larger than the mean value of *DA*.

In Panel B of Table 4, each of the measures for real activities management have significant Pearson (Spearman) correlations with the *INNOV* test variable. The Pearson (Spearman) correlation is also significant (significant for *AbCFO* and *AbDISCEXP*, but not *AbPROD*) for each of the measures of real activities management with the *Bench* indicator variable. The Spearman (Pearson) correlations are also significant for *ABSDA* with both *INNOV* and Bench (significant for *INNOV* but not Bench). In untabulated results regarding the earnings management sample, we find that the average age of IS firms is 15.2 years, while the average age of non-IS firms is 15.7 years. Therefore, on average, an IS firm is on average 3% younger than non-IS firms in the earnings management sample.

Table 5 presents the test results of the association between IS firms and real activities earnings management. The first two columns present the coefficients and t-statistics for Equation (5) with *AbCFO* as the dependent variable, columns 3 and 4 provide results with *AbPROD* as the dependent variable, and columns 5 and 6 present results with *AbDISCEXP* as the dependent variable.

Results indicate that among IS firms, real activity earnings management is present for both the *AbCFO* and the *AbDISCEXP* equations. The dummy variable, *INNOV*, is positive and significant at 0.621 when *AbDISCEXP* is the dependent variable in Equation (5). This indicates that IS firms incur more discretionary expenses than non-IS firms. As is the case in prior literature, firms overall are likely to manage income by manipulating discretionary expenses when close to earnings benchmarks. Consistent with such manipulation, we find a significant negative result for the coefficient of *Bench* at -0.216. Consistent with our hypothesis, we find that IS firms manage income to a greater extent than non-IS firms by decreasing discretionary expenses to increase income as the coefficient for *INNOV*Bench* is also negative and significant at -0.213.

We find similar indications of earnings management by IS firms by testing abnormal cash flows from operations, *AbCFO*. We find using *AbCFO* as the dependent variable in Equation (5) that the coefficient for *INNOV* is -0.255 indicating that IS firms normally have less cash flows from operations than non-IS firms likely due to having incurred more R&D expenses than other firms. Furthermore, IS firms have higher cash flows from operations when earnings are close to zero or approach last year's reported earnings as shown in Table 5 by the significant coefficient of 0.251 for the interaction *INNOV*Bench*. Results for

Equation (5) using *AbPROD* as the dependent variable also indicate real activity earnings management for IS firms. Therefore, our tests regarding *AbCFO* and *AbPROD* provide further evidence for H2.

Table 5 Innovative Strategy and Determinants of Real Activities Earnings Management from 1994 to 2010

Independent variables[a]	*AbCFO* Coefficient (t-statistic)		*AbPROD* Coefficient (t-statistic)		*AbDISCEXP* Coefficient (t-statistic)	
Intercept	-0.290	(-9.24)***	0.044	(1.87)*	-0.126	(-3.31)***
INNOV	-0.255	(-17.63)***	-0.133	(-15.21)***	0.621	(33.05)***
Bench	0.145	(19.95)***	0.024	(4.21)***	-0.216	(-25.12)***
*INNOV*Bench*	0.251	(14.04)***	-0.098	(-7.20)***	-0.213	(-9.40)***
Big	0.267	(26.29)***	-0.042	(-5.82)***	-0.151	(-12.07)***
ChgGDP[b]	-0.000	(-0.01)	0.031	(1.37)	-0.007	(-0.17)
MKTVAL[b]	0.011	(28.11)***	-0.005	(-16.09)***	0.002	(2.58)***
AGE	-0.006	(-8.87)***	0.002	(3.68)***	-0.005	(-5.49)***
MTB	0.004	(5.16)***	-0.002	(-3.87)***	0.002	(1.52)
Industry controls	Included		Included		Included	
Year-by-year controls	Included		Included		Included	
# of observations	11,285		11,285		11,285	
Adjusted R^2	0.298		0.238		0.356	

***, **, * Indicates significance at the 1 percent, 5 percent and 10 percent levels, respectively.

[a]Continuous variables (including dependent variables) have been winsorized at the 1% and 99% levels to ensure results are not sensitive to extreme observations.

[b]Values for this variable have been multiplied by one thousand for ease of interpretation.

Table 6 Innovative Strategy and Determinants of Accrual Based Earnings Management from 1994 to 2010

Independent variables[a]	*ABSDA* Coefficient (t-statistic)	*Positive DA* Coefficient (t-statistic)	*Negative DA* Coefficient (t-statistic)
Intercept	0.919 (6.61)***	0.467 (3.56)***	-0.638 (-5.63)***
INNOV	0.101 (2.93)***	0.062 (1.43)	-0.148 (-4.64)***
Bench	-0.053 (-1.98)**	-0.053 (-1.72)*	0.040 (1.68)*
*INNOV*Bench*	-0.137 (-2.43)**	-0.111 (-1.72)*	0.125 (2.33)**
Big	-0.237 (-7.77)***	-0.193 (-5.87)***	0.221 (7.26)***
ChgGDP[b]	0.161 (1.43)	0.029 (0.32)	-0.255 (-2.04)**
MKTVAL[b]	-0.001 (-1.22)	-0.001 (-0.70)	0.000 (0.24)
AGE	0.002 (0.72)	0.001 (0.42)	-0.003 (-1.50)
MTB	-0.001 (-0.52)	0.001 (0.34)	0.001 (0.58)
Industry controls	Included	Included	Included
Year-by-year controls	Included	Included	Included
# of observations	11,285	6,548	4,737
Adjusted R^2	0.189	0.271	0.155

***, **, * Indicates significance at the 1 percent, 5 percent and 10 percent levels, respectively.

[a]Continuous variables (including dependent variables) have been winsorized at the 1% and 99% levels to ensure results are not sensitive to extreme observations.

[b]Values for this variable have been multiplied by one thousand for ease of interpretation.

Table 6 presents the results of estimating Equation (8) to examine the use of discretionary accruals in IS firms. The first column presents the coefficients and t-statistics *ABSDA* as the dependent variable. The second and third columns present regression results with *Positive DA* and *Negative DA* as the dependent variables.

Overall, the results in Table 6 provide evidence that, in addition to using real activities, IS firms use accruals to manage earnings to a greater extent than do non-IS firms. The coefficient on *INNOV* in Equation (8) where *ABSDA* is the dependent variable is positive and significant at 0.101. This suggests that IS firms use discretionary accruals to manage earnings more than their non-IS firm counterparts thus supporting H3. The coefficient for the interaction term is negative and significant indicating that less accruals are used to manage earnings when the firm's earnings are close to the earnings benchmarks of positive earnings and the prior year's earnings, again supporting H3.

Further, Table 6 provides results of tests for positive and negative discretionary accruals. Table 6 indicates that while the coefficient for *INNOV* with *Positive DA* as the dependent variable in Equation (8) is not significant, the coefficient for *INNOV* with *Negative DA* as the dependent variable in Equation (8) is significant at -0.148 indicating that IS firms utilize less negative discretionary accruals and thus supports H3. The interaction term for positive discretionary accruals is negative and marginally significant at -0.111, and the interaction terms is positive and significant at 0.125 for negative discretionary accruals. These results indicate that while IS firms utilize more discretionary accruals than other firms, it may occur to a lesser extent when IS firms earnings are near the earnings benchmarks of positive income or the prior year's income. This is likely due to a focus on other earnings benchmarks such as analysts' earnings forecasts (DeGeorge, Patel & Zeckhauser, 1999) or targets for specific executive compensation components (Holthausen, Larcker & Sloan, 1995).

3.3 Robustness and Sensitivity Tests

Because both the test variable for IS firms and one of the three discretionary expenses from equation 4 are composed of R&D expenses, we replicate the test regarding abnormal activity for discretionary expenses without including R&D expenses (see Cohen, Dey, & Lys, 2008). In untabulated results we find that upon elimination of R&D expenses from the calculation of *DiscExp*, our conclusions regarding the extent to which IS firms manipulate earnings using discretionary expenses remain unchanged.

To ensure that the results regarding earnings management are not sensitive to particular industries, we replicate the tests for real activities and discretionary accruals without limiting the sample to industries that are R&D intensive. In untabulated results we find no change in the direction or significance level of the test variables in the real activities tests for earnings management. In the tests of accrual based earnings management, we find that the level of significance increases to 1% for the *Bench* variable for all three measures of discretionary accruals and that the level of significance for the interaction variable increases to 5% in the *Positive DA* test and to 1% in the interaction variable in the *Negative DA* test with no change in direction in either case.

We also replicate our results for the earnings management sample for tests regarding real activities management and discretionary accruals including several control variables for executive compensation as in Cohen, Dey and Lys (2008). The additional variables included are defined as follows:

Bonus is the average bonus compensation as a proportion of total compensation received by the CEO and the CFO of a firm;

Ex_Option is exercisable options and is the number of unexercised options that the executives held at year-end that were vested scaled by total outstanding shares of the firm;

Un_Option is unexercisable options defined as the number of unexercised options (excluding option grants in the current period) that the executives held at year-end that have not vested scaled by total outstanding shares of the firm;

Gt_Option is new option grants made during the current period scaled by total outstanding shares of the firm;

Owner is the sum of restricted stock grants in the current period and the aggregate number of shares held by the executives at year-end (excluding stock options) scaled by total outstanding shares of the firm;

Inclusion of these additional controls for executive compensation dramatically reduces the sample size for these tests to 3,199 observations. However, in untabulated results we find that our results and conclusions remain unchanged with the exception of the tests regarding abnormal cash flow from operations which become insignificant.

4 CONCLUSION AND LIMITATIONS

Prior research describes and clearly demonstrates the existence of earnings management (e.g. Burgstahler & Dichev, 1997; Das, Shroff & Zhang, 2009; Degeorge, Patel & Zeckhauser, 1999; Hayn, 1995). The purpose of this paper is to examine the degree to which firms that have a strategy focused on innovation participate in earnings management relative to firms that are not focused on innovation. The association between innovation strategy and earnings management is measured using proxies described in the literature for income smoothing, strategic use of real activities, and the manipulation of discretionary accruals. Consistent with the hypotheses that IS firms smooth earnings, use real activities, and record discretionary accruals to manipulate earnings, the results show that firms with an innovative firm strategy manage earnings to a greater extent than do non-innovation firms. Specifically, the results indicate that innovative firms engage in income smoothing, real activities earnings manipulation and discretionary accruals to meet earnings benchmarks to a greater degree than do non-IS firms.

The results of this paper contribute to the literature by providing additional insight to the understanding of earnings management activity, and will be useful to market participants by specifically documenting the relationship between a firm with an overall strategy focused on innovation and the extent of earnings management. These results also inform managers, regulators, and other stakeholders to be aware that, although the intended outcome of an innovation strategy is normally to increase firm value by marketing new and innovative products or services, an innovation strategy could also affect the way in which income is measured for those firms.

We recognize three limitations to the analysis we perform in this study. First, a large number of observations were eliminated from the sample used in this study due to missing data in the commercial databases employed. This reduction in the sample size could have an impact on the generalizability of the results. Second, although the control variables that were used in all equations for this study were drawn from prior accounting literature, it is possible that relevant controls were omitted from the models. Third, in accordance with U.S. GAAP, the firms included in our sample generally expense R&D costs as they are incurred. Limited exceptions to this rule include the capitalization of software and website development costs. However, capitalization of R&D expenses permitted under other methods of accounting such as IFRS could have an effect on our results, especially as it relates to income smoothing and other earnings manipulation through the alteration of real activities. The potential to capitalize R&D expenses could alter the decisions of management regarding these real activities and could affect the extent to which firms manipulate earnings.

This study concentrates exclusively on innovation strategy. There are a wide range of other firm strategies that have not been examined in this study. Ittner and Larcker (2001) clarify that firm strategies need not be located only on a continuum between firms following a "cost leadership" and firms following an "innovation strategy". Firm strategies can also include higher quality, differentiation through image, superior customer service, a focus on a particular market niche, being flexible in responding to customer demands or mimicking innovations of competitors. Future research could examine the effect of any of these other firm strategies on the extent of earnings management.

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STANDARDS, BEST PRACTICES AND CODES OF ETHICS IMPACT ON IT SERVICE QUALITY – THE CASE OF SLOVENIAN IT DEPARTMENTS

DŽANGIR KOLAR[1]
ALEŠ GROZNIK[2]

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ABSTRACT: *The purpose of this paper is to explore the critical success factors while implementing standards, best practices and codes of ethics, what their benefits are when they are put in place, and how they impact the quality of information technology (IT) services. Through an extensive literature review and interview with experts in the field, we identified instrumental determinants. Structural equation modelling (SEM) was used for the case of IT departments in large Slovenian companies to test the presented hypotheses. The study is based on 102 responses from IT managers in large Slovenian companies. The research findings confirmed a positive correlation between the factors considered.*

Keywords: *standard, ISO, best practices, code of ethics, ITSM, quality of service, SEM*

JEL Classification: M15, L15

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INTRODUCTION

In the global market economy IT as a service has been gaining attention in both practical and theoretical spheres in recent years. While the focus used to be on IT, now it is moving towards services that can be provided with the help of IT (Sandström et al., 2008). IT is relatively new compared to other areas in the company and was merely considered as supporting other functions. Yet, IT is today growing in importance and strategic orientation as it faces challenges. This is best reflected through IT governance which has been gaining ground in practice (Van Grembergen, 2004). In contemporary society, it has never been as important to use international standards (Alič, 2004), best practices (Cater-Steel, Toleman, & Tan, 2005) and codes of ethics (Pivec, 2002). However, not all such efforts yield results. So far, in the literature we can mostly find research confirming positive effects, as well as those without any results or even negative results (Heras, Dick & Casadesús, 2002). The paper's main purpose is to research these trends in the Slovenian environment and ascertain how it impacts service quality in IT departments.

1 University of Ljubljana, Faculty of Economics, PhD Candidate, Ljubljana, Slovenia, email: dzangir@gmail.com

2 University of Ljubljana, Faculty of Economics, Ljubljana, Slovenia, email: ales.groznik@ef.uni-lj.si

Research and literature indicates there is vast interest in this issue. It often happens that expected benefits may not be obtained due to previously listed components not being properly used. An in-depth study shows that all components have a lot in common and it is possible to find a common denominator between them. It is therefore necessary to examine the development of the concepts based on a review of a wide range of relevant literature and to then make a list of standards, practices, codes and dimensions that effect service quality, examine their key success factors in the implementation process, and the benefits they provide once implemented. There are studies that have examined the individual components enumerated above. But so far, in the existing literature we have been unable to find a similar study to the one presented in this paper. The main purpose of this paper is to contribute to current knowledge on service quality with a study of Slovenian IT departments. Therefore, empirical research is required to place attention on the construction of a model for service quality criteria and the key success factors while implementing standards, best practices and codes of ethics.

This paper has the following research objectives: To examine the existing knowledge in the areas of standards, best practices and ethical codes used in the IT field and extract the key characteristics of service quality in IT through a review of the research literature. The paper considers the existing standards, best practices and ethics codes as well as their interactions. It empirically verifies whether there is a link between service quality and the use of standards, best practices and codes of ethics in Slovenian IT departments. It also provides a list of components that affect the quality of IT services, thereby offering guidance to heads of IT departments.

The verification of the hypothesis that the use of standards, best practices and an ethics code in the IT department within Slovenian companies leads to higher quality IT services is an essential contribution. This is especially because this is a relatively new and interesting subject of study, while similar research has yet to be carried out, at least not to such an extent or in the Slovenian environment.

The paper consists of an introductory section, followed by a section with a detailed and critical study of scientific literature where we extract basic definitions of the concepts and summarise the existing knowledge gained from research in the field. The following section defines the purpose and nature of the methodology. The quantitative part is presented through the model and hypotheses. In addition, the process of selecting the variables and the measurement's reliability and validity are described. Results of the quantitative research are described in the Findings section. The hypotheses are verified with a SEM model and the latter is followed by an evaluation of the results and the research theoretical and practical contributions. Unsettled questions, which provide a basis for future research, are discussed in the conclusion.

1 THEORETICAL BACKGROUND

In this section, we present a basic outline of the components studied in the relevant research literature.

1.1 Standards

This paper focuses on ISO standards given that they are internationally established and widely adopted (ISO, 2015). Benefits achieved through certification of ISO standards are lower costs (decrease in risk, maintenance, development time, complaints and scrap) and higher income (increase in productivity, efficiency, customer satisfaction, quality level and marketing effects) (Benefits of Standards, 2015). Critics argue that it reduces creativity (Rebernik, 2000), the implementation is complex and costly (Thomas, 2010), while certificates do not guarantee quality.

ISO 9001

This standard is used in 1,138,155 organisations, 1,672 in Slovenia (ISO Survey, 2015). The ISO 9001 has a focus on the customer and process orientation (Alič, 2008). Research literature suggests certified companies perform better (Chow-Chua, Goh, & Wan 2003; Dimara, Skuras, Tsekouras, & Goutsos, 2004; Corbett, Montes-Sancho, & Kirsch, 2005, Han & Chen, 2007), where the benefits improve over time (Brecka, 1994). Certification by ISO 9001 represents a major competitive advantage (Anderson, Daly, & Johnson, 1999; Naveh & Marcus, 2005). Alič and Rusjan (2003) found that indicators were improved by ISO 9001; higher added value per employee, higher profitability and higher ROA. Pivka and Uršič (2002) extracted three categories of factors that measure ISO 9001 success: quality control, quality assurance and total quality management. Heras, Dick & Casadesús (2002) examined as benefits the lower costs of scrap, better quality and higher revenues. Positive internal (better processes and defined responsibilities) and external effects (access to foreign markets, improved customer satisfaction and responsiveness to market demands) were found in Spain (Casadesus & Gimenez, 2000). The strongest motives for certification in Portuguese companies were to improve quality, reduce costs and obtain market advantages (Santos & Millan, 2013). If the motive is internal (process improvement, lower cost, better quality, employee motivation), it will bring greater benefits than when the motive is external (pressure from government, customers or suppliers) (Singels, Ruël, & Water, 2001; Prajago, 2011; Valmohammadi & Kalantari, 2015).

ISO/IEC 20000

This standard prescribes how to manage IT services by monitoring and controlling processes (ISO, 2015). There is a strong correlation between ITIL and ISO/IEC 20000 (Disterer, 2009). Benefits can be divided into internal and external (Cots et al., 2014).

Supplying services at a reasonable price, solving problems concerning the continuity, availability and performance of services, providing tools for ensuring the quality level, retaining a competitive advantage, and maintaining contracts with customers are the main benefits (da Silva Leite et al., 2014).

ISO/IEC 27000

The standard ISO/IEC 27000 is dedicated to Information Security Management Systems (ISMS) and 23,972 companies are certified under it (58 in Slovenia, 97% in the IT sector) (ISO Survey, 2015). The RIV 2004 survey on information security among Slovenian companies showed that human error accounts for the biggest share of security flaws. An established security policy supported by top management is expected to be crucial for awareness about information security among employees (Einspiler, 2007). Disterer (2012) points out that with the growing importance of IT in today's business environment there is also an increased need for a systematic approach to information security. Wright (2006) suggests it is necessary to measure the effectiveness of security using ISO/IEC 27001 on all levels (management, operational and technical level controls).

ISO/IEC 38500

This standard is based on COBIT best practice. There was no evidence of its use in practice in Slovenia, neither in the available sources nor through our survey.

1.2 Best practices

Best practices are defined as procedures that are generally accepted as good, prescribed or most effective and are not the same for every company (Bogan and English, 1994). In this paper, we will focus on the ITIL, COBIT and project methodologies used in IT.

ITIL

ITIL as a best practice is used for IT Service Management. The most comprehensive studies were carried out in 2010 and 2013 by itSMF (itSMF International, 2010; 2013). The primary reasons for introducing ITIL were: to improve the quality and efficiency of IT services, to reduce both costs and risks, to meet the requirements of businesses with specific IT needs, to adhere to global standards and legislation, and to provide a competitive advantage. The key skills needed for implementation are ITIL Foundation, ITIL Intermediate and Project Management. At itSMF Australia, the benefits of introducing ITIL were studied: defining roles and responsibilities, customer satisfaction, the continuity and availability of services. Identified success factors are the involvement of top management, an effective ITIL champion, the ability of IT staff to adapt to change, along with the quality and capacity of IT staff (Cater-Steel et al., 2005). Iden (2010) made a comprehensive study of the Scandinavian itSMF. The main reasons for introducing ITIL included: a focus on IT services, an increase in professionalism, customer satisfaction, best practice, reduced costs and meeting clients' expectations. Iden and Eikebrokk (2014) found that effectiveness of the group had a greater influence than the involvement of top management. Oražem (2014) confirmed that ITIL helps small and medium enterprises with cloud computing in Slovenia.

COBIT

COBIT 5, unlike similar frameworks, has a wider scope since, in addition to IT management, it covers IT governance. There has been consolidation (Pasquini & Galiè, 2013) with other frameworks and standards in the IT field (ITIL, ISO, PRINCE2...). The purpose is to provide quality information to support business operations and to achieve its strategic objectives, minimise IT risk, optimise IT costs and ensure compliance with laws, regulations and treaties (ISACA, 2015). Preittigun, Chantatub and Vatanasakdakul (2012) examined how research literature and COBIT 5 view IT governance. In a study of 100 articles, they identified articles are mostly concerned with governance (58%), areas of planning (74%) and monitoring (47%). Two years later, Mangalaraj, Singh Taneja (2014) also studied literature on COBIT 5. The research showed COBIT through different perspectives and that the majority of articles concentrated on the overall structure and a comparison with other frameworks (COSO, ITIL and ISO 38500). Some papers, however, dealt with specific COBIT aspects, i.e. safety, risk, systems development, efficiency and internal control. Many published articles related to COBIT are in the field of accounting. The survey results regarding efficiency are not unanimous. Phillips (2013) found a link between COBIT and IT efficiency. Tugas (2010) examined 21 Philippine companies in the food industry and did not find a link between the maturity by COBIT and ROA or ROE. Abu-Musa (2009) found through extensive surveys in Saudi Arabia that for the majority of respondents COBIT had positive effects.

Project management methodologies

While in IT most activities are organised as projects, we also included project management methodologies in the research. We focused on those that are widely accepted, namely PRINCE2 (Patel, 2009) and PMBOK. We also looked at the EMRIS methodology developed in Slovenia. Methodologies comprise a set of principles, processes and tools. The main aspects monitored for ensuring successful projects are budget, time, quality, scope and risks (Bentley, 2015). The biggest reasons for IT projects failing are: absence of clearly defined objectives, an unrealistic financial plan, inadequate staffing, poor communication, poor planning, no monitoring of the project's progress, the scope is not clearly defined, a lack of change control, and no risk management (Graham, 2010). A project managed by PMBOK consists of five processes: Initiating, Planning, Executing, Monitoring and Closing (PMI, 2013). The empirical research that examined project management in practice made some interesting discoveries. The survey showed the most commonly used methodology is PRINCE2. By far the most used tool was Ganttogram. Five key factors that influence the success of the project: clearly defined objectives, realistic timescales, top management support, adequate resources, and commitment/dedication to end users (White & Fortune, 2002). A comparison of the PRINCE2 and PMBOK project management methodology presented their differences and similarities (Matos & Lopes, 2013). PRINCE2 is a prescriptive and PMBOK a descriptive methodology. The PRINCE2 methodology focuses on the product and the PMBOK methodology on processes. The biggest difference between them is that PRINCE2 does not include procurement. In conclusion, the authors prefer the PMBOK methodology.

1.3 Code of ethics

The rapidly developing information society is driven by constant improvements in ICT. These changes are also reflected in the consciousness of individuals and the whole of society. This raises new ethical challenges not covered by the current system of values. The purpose of a code of ethics is to fill the gap between legislation and practice and to help solve ethical dilemmas. Currently, there is no generally accepted code for the IT sector. Tavani (2001) conducted a review of the literature published on the topic of ICT and ethics for the period 1999 to 2001. In addition to this bibliography, he had previously published a bibliography of books and over 200 articles on the same topic. Pivec (2002) deals with the code of ethics in Slovenia. IFIP addresses the new ethical dimensions brought about by IT through a general code of ethics, but quite unsuccessfully. Koehler and Pemberton (2000) propose use of a model code of ethics which could be adapted to an individual environment. For this purpose, they examined and compared more than 50 individual codes of ethics. Bell and Adam (2004) propose including ethics in the educational process. The efficiency of a code of ethics, however, depends on its quality (Erwin, 2011).

1.4 Quality

The view on quality has changed over time (Bergman & Klefsjoe, 1994): from product review, production control, design of products, process management through to total quality management (TQM) at the end. Crosby (1997), Juran (1989) and Deming (1986) define good quality as a predictable degree of uniformity and reliability with requirements or customer needs. Service quality is a comparison between perceptions of the service received and expectations of the service desired (Fitzsimmons & Fitzsimmons, 1998). Service quality is gaining in importance because customers today expect quality services at a reasonable price (Yoo, Kyoon, & Jeong, 2007). The biggest differences between products and services are tangibility, the measurement of quality, and involvement (Gupta & Chen, 1995). Nevertheless, if we want to achieve consumer satisfaction with services and indirectly ensure companies are profitable, it is necessary to investigate the influences and factors important in achieving these objectives (Parasuraman, A., Zeithaml, V., & Berry, 1985). Ghobadian, Speller and Jones (1994) examined models for the quality of services. They considered seven quality models and determined that no model had all necessary components for the management of these services to identify the source of quality, detect problems in quality, determine the cause of the observed problems in quality, and offer possible actions to address them. The service profit chain (Heskett, Sasser, & Schlesinger, 1997) explains the impact of service quality on the financial results. Gummesson's 4Q model defines the services and goods as part of the service. The model has the following variables: *expectation*, *experience*, *corporate image* and *brand*. *Company image* is the same as in the Grönroos model. The variable *brand* adds a new dimension to the model of perceived quality (Gummesson, 1993). In 1988, Parasuraman, Zeithaml and Berry developed a model to measure the quality of services and named it SERVQUAL (SERvice QUALity), where they focus on the fifth gap in the GAP model. Five dimensions of service quality are (Parasuraman et al., 1988, p. 23): Reliability, Responsiveness, Tangibles, Assurance and Empathy. Kang, Caves and Alexandris (2002) adapted the SERVQUAL model to study the needs of internal services. Cronin and Taylor (1992) also argued that SERVQUAL as measured by the ratio between the expected and the perceived service quality is not supported in practice. Therefore, they proposed the SERVPERF model, which contains the same dimensions and focuses solely on the customer's experience when using a service. Caruana and Pitt (1997) developed a scale to measure the quality of internal services called INTQUAL (INTernal QUALity) and examined the link between the quality of service and business impacts in terms of management. Praeg and Schnabel (2006) developed a model called the IT service cachet, designed to assess outsourced IT.

Looking at ITSM (Shahsavarani & Ji, 2014), quality is measured as service efficiency, service quality or by financial indicators. Gacenga, Cater-Steel and Toleman (2010; 2011; 2013) conducted empirical research in the UK, USA and Australia, studied literature and then suggested their measurement model that combines BSC, SERVQUAL and SERVPERF. Lahtela, Jäntti and Kaukola (2010) proposed real-time measurements (ITIL-MS). Hochstein, Zarnekow and Brenner (2005) suggested three areas for measuring ITSM: benefits, costs, and success factors. Hochstein et al. (2004) adjusted SERVQUAL to IT SERVQUAL with 18 its indicators.

2 METHODOLOGY

2.1 Sample and procedures

A survey was conducted among large Slovenian companies as defined by the Companies Act (ZGD-1H, 2009). Empirical data were collected in January 2016 in order to enable the solving of the hypotheses. The source for the list of companies was the Agency of the Republic of Slovenia for Public Legal Records and Related Services (AJPES). In its 2015 database there were 676 companies listed as large according to the Companies Act. Collecting responses was challenging. We retrieved 373 email addresses from AJPES where under a company's entry the main email addresses were provided, not the addresses of IT managers. After researching secondary resources, we collected 555 email addresses. So as to obtain 144 responses (a 25.9% response rate) of which 102 (18.5%) were valid for further research, it was necessary to send emails in three iterations and to refine the mailing list between those iterations.

IT managers were asked to assess how the chosen factors influence the implementation of standards, best practices and codes of ethics in IT departments, which benefits arise from implementation and how it all reflects on the quality of IT services as regarded in their company on five-point Likert-type scales (ranging from 1 for "not important at all" to 5 for "very important"). The tool used for this survey was 1KA, an online survey portal run by the Faculty of Social Sciences at the University of Ljubljana. Questions used in the survey were adapted from previous works on standards (Alič, 2013; Buttle, 1997; Cots, 2014; da Silva Leite et al., 2014; Disterer, 2012; Disterer, 2013), best practices (White & Fortune, 2002; Cater-Steel et al., 2005; Groznik et al., 2010; Iden, 2010; itSMF International, 2013; Ahmad & Shamsudin, 2013; Mangalaraj et al., 2014) and codes of ethics (Koehler & Pemberton, 2000; Pivec, 2002). The questionnaire was divided into three sections. The first and last were designed to collect data about descriptive statistics and demographics of the companies and IT managers. The main section of questionnaire included questions about key success factors in the implementation of standards, best practices and codes of ethics, benefits of that implementation and how they are reflected in the quality of IT services perceived by end users. A pilot survey with an interview was conducted with ten experts (five academics and five experts) for the purpose of evaluating the questionnaire. Comments and suggestions made formed the basis for revising the questions before the questionnaire was sent to the target population.

2.2 Method

For conducting descriptive statistics and exploratory factor analysis (EFA) we used the software package IBM SPSS Statistics version 20. For confirmatory factor analysis (CFA) and structural equation modelling (SEM) we used the software package IBM SPSS Amos version 22 in order to present structured connections among the factors for implementing standards, best practices and codes of ethics in IT departments, their impact on ITSM and the company's internal IT services quality assessment.

2.3 Hypotheses

A review of research literature yielded conclusions that were synthesised into the seven hypotheses stated below.

Hypothesis 1: Use of the standards/best practices has a positive impact on the IT service quality.

Hypothesis 2: Use of a code of ethics has a positive impact on the IT service quality.

Hypothesis 3: Personnel have a positive impact on the implementation of a standard or best practice.

Hypothesis 4: The motive for implementing has a positive impact on the implementation of a standard or best practice.

Hypothesis 5: Top management's involvement has a positive impact on a standard or best practice.

Hypothesis 6: Top management's involvement has a positive impact on the code of ethics.

Hypothesis 7: Composition of the code has a positive impact on the implementation of the code of ethics.

2.4 Identification of determinants in the model

Special attention is paid to the definition and operationalisation of concepts covered in the model. The operationalisation is performed by means of a research comparison of already verified questionnaires and tested with findings of qualitative research using semi-structured interviews with two groups of respondents, IT specialists and academics in the IT field. Among the main sources of the key success factors and benefits was the research by Iden (2010; 2014), Cater-Steel et al. (2005), Groznik et al. (2010) and itSMF (2010; 2014) while, for the code of ethics Pivec (2002) and for quality we used the dimensions from SERVQUAL (1988, Parasuraman et al., 1988) and SERVPERF (Cronin & Taylor, 1992).

We had to consider some limitations. Being able to measure the latent construct in the SEM model requires at least two variables per construct. On the other hand, if we had used too many variables, the survey would have been too long and respondents would have been unwilling to complete the survey. In the end, we assembled questionnaire with 49 items. For all items, we used a five-level Likert scale as the method for evaluating the determinants.

For the construct *Personnel* we measured the importance of human resource aspects while implementing a standard or best practice. We measured the importance of a good project manager, the right people in the right positions, the fluctuation of key people, process thinking of the team, knowledge of the team, the team atmosphere, team effort and employee readiness to accept change.

The construct *Motive* was measured with variables including external (image, competitive advantage, legislation, partner requirements) and internal motives (risk reduction, quality improvement, efficiency improvement and cost reduction).

The construct *Top management* measured the role of management when implementing standards/best practices and the code of ethics with variables, the setting of clear objectives before initiating the project, the establishing of realistic expectations about the project, allocating the necessary resources for the project, actively participating in the problem resolution, monitoring and evaluating the project from beginning to end, support for the project from start to finish, setting an example with their actions, accepting responsibility, establishing a clear mission, values and principles of the organisation.

The construct *Content* was measured with variables taking account of the mission, values and principles of the organisation, defining company policy and how to deal with breaches of the code, and whether it is in accordance with the law, defines personal responsibility, defines the confidentiality of information, defines a conflict of interest, defines the relationship to the environment, and includes current ethical challenges in the IT field.

The construct *Code of ethics* measured the effectiveness of the latter with the variables image, communicating values to all stakeholders, facilitating decision-making of employees in ethically challenging situations, consistency of operations, and degree of compliance with the legislation.

The construct *Standard/Best practice* measured the effectiveness of the latter with variables of processes regulation, the definition of roles and responsibilities, improvement in risk management, improvement in the quality of IT services, reduction of the cost of IT services, and customer satisfaction with IT services.

The construct *IT service quality* was measured with the SERVQUAL/SERVPERF dimensions such as variables reliability, assurance, tangibles, empathy and responsiveness.

3 FINDINGS

By conducting the survey, we acquired valuable data for studying the factors of implementing standards, best practices and codes of ethics and how they impact the quality of IT services. In this section, we start by examining characteristics of the participating IT managers and the organisations where they work. We proceed with exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Finally, structural equation modelling (SEM) was created where the relationship between the use of standards, best practices and codes of ethics vis-à-vis IT services was tested.

3.1 Sample analysis

In Table 1 (in the appendix) a summary is provided of the sample's main characteristics. Among participating companies, the highest share of participants was in the manufacturing sector (23.5%). That was expected since they are the most represented sector in the whole population. They are followed by the Financial and ICT sectors. But if we look at the ratio between all big companies in an individual sector and those participating in the survey we can see we obtained a response from 42% of all ICT companies, whereas in the other sectors this share was between 10% and 15% (AJPES, 2015).

The next relevant characteristic is that more than half (56.9%) of the companies are situated in Central Slovenia. This shows that the country is very centralised in terms of the distribution of companies among regions. The population of large companies (ZGD-1H, 2009) in Slovenia is made up of those with more than 250 employees, revenue exceeding EUR 35 million, assets of more than EUR 17.5 million, have consolidated balance sheets or are from the financial sector (banks, insurance companies and stock exchange). From the sample population we can see that most respondents have between 251 and 1,000 employees (45.1%), followed by those with up to 250 employees (38.2%), some of them had between 1,001 and 5,000 employees (12.7%) and few had more than 5,000 employees (3.9%).

The number of employees in IT for those companies ranges from 0 (IT is completely outsourced) to 230, with an average of 18.2. IT is chiefly organised in a separate department (69.6%) or as part of a bigger department, i.e. Operations (13.7%). To a small extent, IT is handled by individuals or is completely outsourced (7.8%). In one case, nobody is formally in charge of IT. The highest position held by an IT employee is mainly a department manager who is directly responsible to the Board, with a tactical level of decision-making (44.1%). They are followed by those who form part of top management (CIO), with a strategic level of decision-making (30.4%). To a lesser extent, department managers were at the operational level (16.7%) or where there is nobody in a management position (8.8%). Further, gender inequality is clearly shown in that in IT management positions males dominate with 87.3% and females are represented with just 12.7%. These management positions are assigned to experienced (96.1% are older than 30 years) and educated (54.9% hold a Master degree) individuals.

In the sample of 144 respondents, 102 had used at least one of the standards, best practices or codes of ethics listed in Table 2 (appendix). More than half have the ISO 9001 certificate (55%) or an internal code of ethics (56%). The second standard is the ISO/IEC 27001 (16%) that is used primarily by the ICT and Finance sector companies. It is followed by ISO/IEC 20001 (4%), which is higher than expected given that before the survey we could only find one company certified for this standard in Slovenia. None of the companies was certified for the final standard, ISO/IEC 38500. This was expected since this it is the newest standard in the survey and in other countries it is generally implemented by companies that exceed Slovenian large companies in size. Among best practices, ITIL is implemented in 16% of companies, COBIT in 3% and CMMI in none. The PMBOK project methodology is used in 7% of companies; both PRINCE2 and EMRIS are used in just one company.

Most of these findings are not surprising, they are expected and correlate with findings in the literature (Groznik et al., 2010). One fact causing concern is that there is not enough knowledge even about the terminology in the field. There is a possible reason for the low level of implementing those standards, best practices and codes of ethics.

3.2 Exploratory factor analysis (EFA)

We used exploratory factor analysis to reduce the number of variables only to those that are significant (Hair et al., 2009). In this way, we simplified the complexity of the connections between the observed variables and factors.

The first step was data screening. In this process, we removed 42 responses out of 144 that have not implemented any of the standards, best practices or codes of ethics. Then we replaced the values that are missing with the median value for specific variables. In addition, one respondent answered all the questions with the same answer and was thus removed before proceeding with the EFA.

We conducted an exploratory factor analysis and confirmed seven factors and named them Personnel, Motive, Top management, Content, Standard/Best practice, Code of ethics and IT service quality according to our hypotheses. From the 49 variables we selected 19 that were most significant (with the lowest value of 0.674). In the exploratory factor analysis we chose the Maximum Likelihood (ML) method. Metric constructs were obtained by using a Promax rotation and with a Scree plot.

With the use of statistical tests – the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's Test of Sphericity – we determined whether the link between the observed variables can be explained by the smaller number of indirect observable variables obtained at the end of the factor analysis and that the data are suitable for further analysis. With a KMO value of 0.721, we exceed the 0.5 threshold proposed in the literature and the significance for the Bartlett's test was below 0.001 ($\chi 2$ = 1338,545, df = 171, Sig = 0.000). Cumulative variance explained by factors using the selected variables was 82.6%, meaning the values of these results for those indicators were acceptable to proceed with the Confirmatory Factor Analysis.

3.3 Confirmatory Factor Analysis (CFA)

The model factors were then tested using Confirmatory Factor Analysis. In doing so, we checked whether the individual latent variables explained the observed variables. Finally, we looked at various compliance indicators where we tested the quality of the measurement model. The composite reliability indicators (CR) exceed the threshold value of 0.7, confirming internal consistency. The average variance extracted (AVE) for all factors is higher than the 0.50 threshold proposed in the literature (Fornelli & Lacker, 1981). This means the instrument's high level of reliability in terms of internal coherence and standardised regression weights.

3.4 Model Fit Summary

In structural equation modelling we establish whether the model is acceptable with the fit indicators. In the literature, we can find many different indicators with different threshold values for those indicators that are acceptable for a good model fit. So we relied on several indicators that are used in practice (Marsh & Hau, 1996; Jaccard & Wan, 1996). Basic indicators are $\chi^2 = 153.307$, df= 131, $\chi^2/df = 1.170$, a value between the threshold values 1 and 3. The Comparative Fit Index (CFI) is 0.891 and GFI is 0.841, they are close to the threshold value of 0.9 suggested in the literature (Hu & Bentler, 1998). The Root-Mean Square Error of Approximation (RMSEA=0.041) is below the suggested cut-off value of 0.05 for a good fit model. All chosen indicators show that the model has a fairly good fit and is specified correctly.

3.5 SEM model

After determining that the model is a good fit, we then established whether specific paths in the model are significant. Hypotheses were tested with the SEM model on the factors' direct and indirect impact and the benefits on IT service quality.

As evident from the research model (Figure 1), the connection between standards/best practices and IT service quality is moderate (0.25), positive and statistically significant ($p < 0.05$), so we confirmed Hypothesis 1. The higher the performance of standards/best practices the better the IT service quality. This is also evident in the theory.

The connection between a code of ethics and IT service quality is moderate (0.32), positive and statistically significant ($p < 0.005$), allowing us to confirm Hypothesis 2. The higher the performance of the code of ethics the better the IT service quality. This is also evident in the theory.

The connection between personnel and standard/best practice is moderate (0.33), positive and statistically significant ($p < 0.005$), so we confirmed Hypothesis 3. The better we employ personnel during implementation the better results of the standard/best practice will be. This is also evident in the theory.

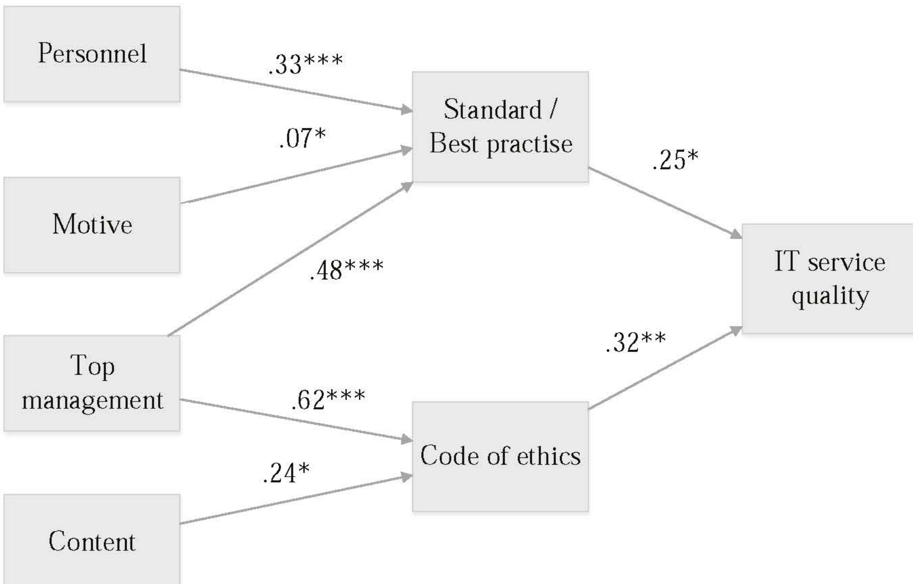
The connection between motive and standard/best practice is weak (0.07), positive and still statistically significant ($p = 0.05$), permitting us to confirm Hypothesis 4 with some consideration, but the connection is too weak and we are therefore ultimately rejecting it. Choosing the right motives to implement a standard/best practice will have only slightly better results than the standard/best practice. These findings are opposite to the theory and research conducted previously.

The connection between top management and a standard/best practice is strong (0.48), positive and statistically significant ($p < 0.001$), so we confirmed Hypothesis 5. The better we employ personnel during implementation the better the results of the standard/best practice will be. This is evident in the theory.

The connection between top management and a standard/best practice is very strong (0.62), positive and statistically significant (p <0.001), allowing us to confirm Hypothesis 6. The more involved top management is during the implementation, the better the results of the code of ethics will be. This is also evident in the theory.

The connection between content and a code of ethics is moderate (0.24), positive and statistically significant (p <0.05), permitting us to confirm Hypothesis 7. The better we prepare the content during implementation the better the results of the code of ethics will be. This is also evident in the theory.

Figure 1: The proposed SEM model for the impact of standards, best practice and codes of ethics on the quality on IT service quality, Slovenian big companies



* significant at the 0.05 level, ** significant at the 0.005 level, *** significant at the 0.001 level

With these results for the SEM model all hypotheses were confirmed, only with Hypothesis 4 is it rejected since the influence is weak.

4 DISCUSSION AND CONCLUSIONS

The empirical part of the paper is followed by the evaluation below in terms of both theory and methodology. We first outline relevant contributions which represent our theoretical and empirical findings. Some open issues are discussed which provide opportunities for future work in this field.

4.1 Theoretical contributions

The main novelty of the present paper is the proposed SEM model. In the above sense, our research findings expand knowledge related to IT service quality. With this SEM model we explore the direct and indirect connection and impact of factors. Practical implications of the research are discussed in the next sub-section.

4.2 Practical implications

With our studies in this paper we have established that the use of standards, best practices and codes of ethics holds direct and positive potential for the quality of IT services. Through correct implementation of standards, best practices and a code of ethics, companies will increase their ITSM performance, ethical behaviour and internal satisfaction with IT services. We can see that most large companies are still using just the general ISO 9001 standard and a code of ethics for the entire company. There is a lot of room for improvement. If these companies wish to remain competitive in future, they need to make some extra effort while implementing the standards, best practices and the code of ethics related to IT. When they decide to take that step it is important to do it with proper preparation, use the right resources and for the right reasons. When they are correctly put in place, there will be positive results reflected in end user satisfaction with IT services. On the other hand, the research results of this paper will give them some guidelines when they start to pursue these goals.

4.3 Limitations and future research

Generalisation of the research results is reduced by certain limitations. The 102 companies included in the sample represent 15% of the whole population. Still, comparing the sample characteristics with those of our population, there are some differences. This study was made on a sample from Slovenia so it should be used for comparison with similarly sized economies. While in most literature on statistical analysis 100 units is perceived as sufficient for the SEM model, some suggest up to 200 units as optimal (Klem, 2000). However, we can also find examples of SEM research with just 60 (Mihalič & Buhalis, 2013) or 70 (Zebec-Koren, 2010) units. Taking this limitation into account, it can be interpreted as a subjective evaluation of IT managers regarding the variables in the survey.

Potential for future research runs in many directions. One possibility is to widen the population to companies in other countries or to even make the research global. The second would be to make it longitudinal and the research could then show how variables are affected by duration of the implementation period. As evident from the descriptive characteristics of the population, we still have a percentage of adopted standards, best practices and codes of ethics specialised in IT. Research into the reasons for the current situation and possibilities to improve it is another topic that should be explored. The last one is to look partially at one pair of components, i.e. how standards influence each other or the link between standards and best practices or standards and codes of ethics.

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APPENDIX

Table 1: Characteristics of the sample used in the research

INDUSTRY					%
	Manufacturing				23.5
	Electricity, gas, steam and air conditioning supply				5.9
	Construction				8.8
	Wholesale and retail trade; Trade; Repair of motor vehicles and motorcycles				11.8
	Transportation and storage				2.9
	Accommodation and food service activities				2.0
	Information and communication				11.8
	Financial and insurance activities				17.6
	Professional, scientific and technical activities				4.9
	Administrative and support service activities				2.0
	Public administration and defence				1.0
	Human health and social work activities				2.0
	Other				5.9
Region					
	Mura				2.9
	Drava				7.8
	Savinja				10.8
	Central Sava				2.0
	Lower Sava				1.0
	Southeast Slovenia				2.0
	Central Slovenia				56.9
	Upper Carniola				8.8
	Littoral–Inner Carniola				1.0
	Gorizia				4.9
	Coastal–Karst				2.0
Number of employees					
	Up to 250				38.2
	251 to 1000				45.1
	1001 to 5000				12.7
	Above 5000				3.9
Number of employees in IT					
	Average	Std.Dev	Maximum	Minimum	
	18.2	36.97	230	0	
How IT is organised					
	Separate department				69.6
	Part of a bigger department (i.e. Operations)				13.7
	Individuals take care of IT				7.8
	Outsourced IT completely				7.8
	Nobody is formally in charge of IT				1.0

Highest position held by IT person		
	Top management, CIO, strategical level	30.4
	Department manager, directly under the Board, tactical level	44.1
	Department manager, indirectly under the Board, operational level	16.7
	Nobody has a management position	8.8
Gender		
	Male	87.3
	Female	12.7
Age group		
	up to 30 years	3.9
	31–40 years	28.4
	41–50 years	39.2
	51 years or more	28.4
Education level		
	High school	6.9
	Bachelor degree (Bologna system)	20.6
	Master degree (Bologna system)	54.9
	PhD	17.6

Table 2: Application of standard, best practices and code of ethics in Slovenian large companies

	Not familiar with term	Familiar with term but do not apply it	Plan implementation	In Implementation phase	Already implemented
ISO 9001	8%	32%	2%	3%	55%
ISO 20001	24%	63%	7%	2%	4%
ISO 27001	12%	55%	13%	4%	16%
ISO 38500	44%	52%	3%	1%	0%
ITIL	18%	52%	8%	8%	14%
COBIT	28%	59%	8%	2%	3%
CMMI	63%	35%	2%	0%	0%
PRINCE2	47%	47%	3%	2%	1%
PMBOK/PMI	54%	35%	3%	1%	7%
EMRIS	67%	30%	1%	1%	1%
ACM Code of Ethics	68%	28%	1%	1%	2%
In-house Code of Ethics	16%	20%	3%	5%	56%

Table 3: Pattern Matrix

	Factor						
	1	2	3	4	5	6	7
Q14f	1.041						
Q14c	.755						
Q14a	.674						
Q19a		.962					
Q19c		.905					
Q19d		.720					
Q17d			.956				
Q17a			.886				
Q17b			.701				
Q12h				.862			
Q12b				.857			
Q12a				.812			
Q13f					.990		
Q13e					.799		
Q16d						.908	
Q16e						.786	
Q18d							.796
Q18c							.746
Q18b							.692

Extraction Method: Maximum Likelihood
Rotation Method: Promax with a Kaiser Normalisation
a. Rotation converged in 6 iterations

EXPLORING THE INTERPLAY OF AN ENTREPRENEUR'S THINKING, KNOWLEDGE, AND FIRM-LEVEL INNOVATION

MIHA PREBIL[1]
MATEJA DRNOVŠEK[2]

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ABSTRACT: *This study investigates entrepreneurs' individual characteristics in terms of knowledge and thinking skills to better understand the role of these traits in innovation. We use interpretative phenomenological analysis (IPA) to attain deeper insights about entrepreneurs' cognitive processes and innovation. We propose that knowledge breadth plays an enhancing role in the relationship between an entrepreneur's knowledge depth and firm innovation. In return, innovation at a firm level is shown to be affected by an entrepreneur's integrative thinking ability. Implications for practice and future research are discussed.*

Keywords: *knowledge breadth, knowledge depth, integrative thinking, innovation, SMEs*
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INTRODUCTION

The more extensive a man's knowledge of what has been done, the greater will be his power of knowing what to do. Benjamin Disraeli (1804–1881, British Prime Minister)

This quote by Benjamin Disraeli indicates the important role of knowledge, experiences, and accumulated skills in dealing with unknown situations. Its meaning can be easily reflected in entrepreneurship, where entrepreneurs tackle problems they have never experienced before with their own knowledge base and methods in order to provide an innovative solution. The impact of knowledge (Dakhli & De Clercq, 2004; Davidsson & Honig, 2003) and an entrepreneur's thinking (Baron, 1998; Krueger, 2007) on different entrepreneurship outcomes has been widely explored in prior literature. The significant impacts of these characteristics in entrepreneurship, such as creativity (Shalley & Gilson, 2004), firm performance (DeCarolis & Deeds, 1999), and innovativeness (Marcati et al., 2008), have long been delineated. However, we still do not have a good understanding of how aspects of an entrepreneur's cognition interact in influencing firm-level innovation. Correspondingly, we are interested in an individual's narrative about innovation.

1 Centre of Excellence for Bionsensors, Instrumentation and Process Control-COBIK, Ajdovščina, Slovenia, e-mail: miha.prebil@cobik.si

2 University of Ljubljana, Faculty of Economics, Ljubljana, Slovenia, e-mail: Mateja.drnovsek@ef.uni-lj.si

An individual's knowledge serves as a prerequisite base for discovering and exploiting opportunities (Gupta & Govindarajan, 2000; Wiklund & Shepherd, 2003) and represents a foundation on which innovation can be built (Nonaka et al., 2000). Authors such as Price et al. (2013) suggest a positive relationship between knowledge and innovation, and recognize knowledge as a vital part of innovative activity (Cohen & Levinthal, 1990; Martín-de-Castro et al., 2008). Scholars distinguish between different types of knowledge. Rather than studying a firm's accumulated knowledge, this research focuses particularly on knowledge at the individual level of an entrepreneur, specifically its breadth and depth, and the effect these domains have on firm innovation. The first refers to the range of different areas in which a firm has expertise, whereas the latter indicates the amount of within-field knowledge (Prabhu et al., 2005). Drawing from existing literature, our particular interest concerns exploration of individual as well as interactive effects of both dimensions – depth and breadth – on innovation.

In addition to an entrepreneur's knowledge, we also aim to explore entrepreneurs' thinking patterns to reveal components that lead to innovativeness. We base our research on a theory by Martin (2007b), who claims that successful entrepreneurs are competent integrative thinkers, and explore the contribution of such a thinking style to innovation. Martin defines integrative thinking as "the ability to face constructively the tension of opposing ideas and, instead of choosing one at the expense of the other, generate a creative resolution of the tension in the form of a new idea that contains elements of the opposing ideas but is superior to each" (Martin, 2007b, p. 15).

We seek to verify empirically the importance of an entrepreneur's integrative thinking for innovation. The concept derives from observation, and we begin by exploring entrepreneur attributes that characterize innovativeness. By identifying the emerging themes that delineate thinking that fosters innovation, we reveal the resemblance to the theory of integrative thinking. In response to the limited studies in the field, we utilize qualitative research methods to develop a deeper understanding and rich descriptives of entrepreneurs' perceptions and behaviour in relation to firm-level innovation (Patton, 2002). A novel interpretative phenomenological analysis (IPA) is used to explore how entrepreneurs perceive different situations they are facing in the innovation process, how they make sense of the surrounding factors, and what meaning they attribute to underlying cognitive attributes (Smith et al., 1997).

In this study we focus on small and medium-sized enterprises (SMEs) entrepreneurs. We demonstrate that SMEs' innovation can be attributed largely to the knowledge and thinking of the entrepreneurs who run them, rather than being a cumulative effect of all employees. Generally speaking, SMEs provide an interesting field of research because they are essential to the economy (Drilhon & Estime, 1993) and have become a driving force for technological progress, economic growth, and overall competitive development (Lin, 1998; Thornburg, 1993).

1 LITERATURE REVIEW

1.1 Knowledge breadth and knowledge depth

This research focuses on two dimensions of personal knowledge: depth and breadth. In the literature, knowledge depth is described as the degree of expertise one possesses, whereas knowledge breadth refers to a broad understanding of other disciplines (Brown & Katz, 2009). To date, the knowledge dimensions of depth and breadth have been studied only at a firm level. Authors have looked at the problem from various perspectives. Marvel and Lumpkin (2007) proved the positive effect of experience depth on innovation radicalness, whereas Prabhu et al. (2005) show that firms with a deeper knowledge are more innovative in terms of patent numbers. Similarly, a recent study by Carlo et al. (2012) examined a knowledge-based model of radical innovation in the field of IT. It shows an important role of knowledge depth and knowledge diversity of a firm in the level of radical innovation. However, more studies are needed to explore in detail the interplay between entrepreneur knowledge depth and breadth and the overall contribution of these domains to firm innovation.

Interestingly, the effect of knowledge depth is not self-evident. There is evidence of both negative and positive influences on innovation. Nowadays, narrow specialization tends not to be sufficient – emphasizing one specific area of expertise and lacking the adaptive ability to advance in different fields might cause firms problems handling different situations which require diversified knowledge, through the institutionalizing of core rigidities resulting in inhibition of innovative activity (Leonard-Barton, 1995). Specifically, experts typically possess many experiences and skills and much knowledge in their areas of expertise. Their focus becomes a specialized niche. Therefore they suffer from an "expert syndrome", which inhibits their creativity (Dean, 1999). It describes the experts' usual negligence of other domains outside their specialization. Evidently, there exists the unconditional need for knowledge diversity and, consequently, knowledge breadth. Scholars (e.g., Bierly & Chakrabarti, 1996; Cohen & Levinthal, 1990) stress the importance of knowledge diversity for creativity and innovation, which also represents a basis for strategic advantage, and of the ability to integrate knowledge across different scientific knowledge bases outside and inside the firm's main scope, for better performance and innovation (Henderson & Cockburn, 1994; Pisano, 1994).

Boosting knowledge breadth and depth in a complementary rather than a substitutive way might be crucial for a firm's success. Along with this assumption, Dewar and Dutton (1986) stress the importance of knowledge depth and diversity for innovation. So an entrepreneur must possess the highest level of both knowledge domains. Prabhu et al. (2005) also suggest that breadth of knowledge increases the possibility for "happy accidents", which may originate as a result of concept application from one field across different disciplines. Likewise, van Wijk et al. (2012) indicate the necessity of balanced knowledge for enhanced innovation performance – knowledge depth is shown to contribute to exploitative and exploratory innovations, whereas knowledge breadth impacts solely exploratory innovations.

It is evident that companies that generate knowledge from a vast foundation are more productive (Henderson, 1994). Bierly and Chakrabarti (1996) emphasize the role of knowledge breadth, because such a knowledge base provides more options to transform related technologies in new, unexpected ways, which eventually increases the sustainability of competitive advantage (Reed & DeFillippi, 1990). Many researchers provide explanations of the positive role of the integration of different fields of expertise (Henderson & Cockburn, 1994), especially in technical industries. They mention that deep expertise in one field and integration of a wide range of disciplines increases the competitive edge of a firm. In order to stay in the market within a certain discipline, firms have to broaden their areas of specialization. Prabhu et al. (2005) show that greater breadth of knowledge leads to increased innovation. Similarly, Cohen and Levinthal (1989) recommend a greater number of fields of knowledge in order for a firm to be more innovative.

Building on such theories as that human capital positively affects firm innovation (Dakhli & De Clercq, 2004; Popadiuk & Choo, 2006) and that depth of technical experience and education is positively related to innovation radicalness (Marvel & Lumpkin, 2007), we can assume also that entrepreneur knowledge – specifically, its breadth and depth – positively affects innovative activity of a firm. Deriving from the previous discussion, we can postulate that human capital in SMEs is largely represented by the entrepreneurs who run them, so their knowledge may have a positive effect on innovation. In other words, the knowledge set of an entrepreneur may provide a foundation on which a firm is able to innovate (Nonaka et al., 2000).

We build our research questions on the assumption of the prevailing role of entrepreneurs in the decision-making processes of SMEs (Lin, 1998; Torres & Julien, 2005). We use this role to create a parallel between the connection between firm-level knowledge and innovation and the connection between a manager's/entrepreneur's knowledge and firm innovation. The focus on the relationship between an entrepreneur's individual-level characteristics and firm-level innovation output is of a particular importance in the context of SMEs, because it has been shown that entrepreneurs are vital drivers of firm innovation (Marcati et al., 2008). Amabile et al. (1996) suggest that innovation begins with creative ideas by individuals and teams within an organization. Whereas large firms are managed by professionals, SMEs usually are owned and run by founders (Lu & Beamish, 2006; Shuman & Seeger, 1986). The latter are less comprehensive in their decision behaviour, and thus should possess more diversified knowledge (Smith et al., 1988), because their behaviour otherwise might have negative consequences for the enterprise's performance (Lu & Beamish, 2006). Moreover, firm performance, development, growth, and innovation are said to be a reflection of an entrepreneur's characteristics, actions, effectiveness, and behaviour (Baron, 2013; Hmieleski et al., 2015; Lin, 1998). North and Smallbone (2000) show the central role of an entrepreneur in the initiation and development of innovation. In their study, an entrepreneur was often also the only person involved in the innovation process of a firm.

Building on prior literature, we define the scope of our research by posing the following questions:

How does an entrepreneur's knowledge affect innovation?
How do knowledge breadth and knowledge depth influence each other?
How does the combination of knowledge breadth and knowledge depth impact firm innovation?

1.2 Entrepreneurs' integrative thinking

Another important attribute successful entrepreneurs have been shown to exhibit is integrative thinking (Martin, 2007b). Integrative thinking illustrates a manner in which entrepreneurs solve problems. Effective use of such thinking brings their firms to a higher level of performance and innovation.

According to Martin (2007b) the process of integrative thinking consists of four steps. These stages do not differ tremendously from conventional business thinking; rather, it is the way in which integrative thinkers approach them that makes a difference. In determining salience, an integrative thinker, in contrast to a conventional thinker, searches for less obvious but potentially relevant factors. When analysing causality, not only linear relationships between variables are considered but also multidirectional and nonlinear relationships. A third step, employment of a holistic approach to the problem, is crucial. Resolution is later achieved by resolving tensions between opposing models.

In the following paragraphs we review the steps of the process in depth and examine their individual contributions to innovation. For the purposes of innovation it is crucial to determine real market needs, develop a deep understanding of the consumer, and then to comprehend all the fragments that compose a problem (Brown & Wyatt, 2010; Nussbaum, 2004; Sakkab, 2007). Integrative thinkers exhibit an ability to see all the salient aspects of the problem and seek less obvious but relevant factors (Brown, 2008, p. 87; Martin, 2007a, p. 66, 2007b, p. 47). This advantage might have a parallel in an organizational construct of absorptive capacity. In order for firms to be innovative, they require an ability to recognize new and useful external information, assimilate it, and then use it for commercial purposes (Cohen & Levinthal, 1990). Such characteristics are suggested to have an important effect on innovation (Fabrizio, 2009; Murovec & Prodan, 2009; Tsai, 2006), because more-relevant information can be gathered externally and used appropriately in problem solving. Because our focus is on SMEs, where an entrepreneur's decisions usually also represent the firm's decisions (Carrier, 1994; Torres & Julien, 2005), we postulate that the same features also apply to entrepreneurs.

Entrepreneurs further differ in mechanisms for analysing causality. To make a good decision later on, a proper analysis of the salient features and how they relate to each other must first be made. Conventionally, entrepreneurs seek an easy way out and are happy with simple linear relationships. On the other hand, integrative thinkers consider all relationships between variables. This step is grounded in generative reasoning, which helps to provide a foundation for creative resolutions. To put it differently, it is the process of using abductive logic, which successfully operates with novel and interesting data

(Ambrose & Harris, 2009, p. 43). When solving difficult problems, integrative thinkers need to look at everything, because a potentially omitted part could lead them to solution. Abductive logic is a tool for discerning a pattern out of the mystery (Martin, 2007b, 2009, p. 74). After an observation of an unpredicted phenomenon is made, abduction is used to find answers because it is perfect for managing incomplete information (Arrighi & Ferrario, 2008; Hintikka, 1998). In addition, an important feature of generative reasoning is also a trial-and-error concept, which is shown to foster innovation (Cannon & Edmondson, 2005; Thomke, 2003). In summary, abductive thinking, by generating new hypotheses and new outcomes, fosters creativity and innovation (Gonzalez & Haselager, 2005; Ross, 2010).

After causal relationships between salient features have been established, a decision needs to be made. Entrepreneurs usually lose sight of a problem, which results in mediocre results. Integrative thinkers, on the other hand, keep the whole problem architecture in mind to see how different parts fit together and how decisions will affect one another. A third differentiation from conventional thinking is the use of a holistic approach.

Integrative thinkers create a holistic architecture in a search for creativity (Ambrose & Harris, 2009; Martin, 2007b, p. 82). They avoid conventional thinking by using segmented analyses, and by keeping the entire problem in mind while working on its parts they are able to examine the mutual effects of single parts (Brown & Katz, 2009; Martin, 2007a, pp. 65-67). Holistic thinking enhances understanding of the relationships between parts within the context of the system. This style creates the foundation for a greater innovativeness and innovation, because problem defragmenting is not optimal for solving tough problems – Martin (2007b, p. 79) argues that there exist only business decisions, not finance, marketing, and other decisions. A problem must be seen as a whole, and segmented specialists (e.g., R&D, marketing, human resources) do not have much knowledge in other fields and therefore frequently reject decisions other than their own. Other divisions then have to try their best within limits. Many other scholars (e.g., Cooper & Edgett, 2008; Desbarats, 2005) agree that a holistic approach has become a new imperative for better innovation processes and therefore for achieving a competitive edge.

In achieving resolution, entrepreneurs too often accept unpleasant trade-offs and settle for the best alternative. The reason lies in their tendency to simplify, which causes ignorance of possible opportunities, which emerge when examining problem features in the previous stages. By contrast, should there exist tensions between opposing ideas, integrative thinkers are prepared to solve them and generate innovative outcomes (Martin, 2007a). It is no problem for them to examine everything again at the end of the process and find a way to integrate all features in a nonconventional, superb, innovative outcome.

Prior literature suggests that the steps that form the integrative thinking process have a positive effect on innovation individually. Building on prior knowledge suggesting a strong linkage of entrepreneur behaviour in fostering SMEs' innovation (Marcati et al., 2008), we expect that entrepreneur thinking enhances firm innovation. This study explores factors that determine how their thinking leads to innovation, determines how successful entrepreneurs act, and examines a possible linkage of these attributes with the characteristics of integrative thinking. The aim is to reveal prevailing factors of entrepreneur thinking skills that affect innovation and verify whether these factors actually characterize integrative thinkers, which are said to be the new imperative in business. To set the context of our research we pose the following questions:

What are the key determinants of an entrepreneur's thinking that enhance his/her problem-solving skills?
How does an integrative-thinking entrepreneur differentiate from other entrepreneurs?
How does an integrative-thinking entrepreneur affect firm innovation?

2 RESEARCH DESIGN

This article develops a deep understanding of how an entrepreneur's knowledge dimensions and integrative thinking interact to impact firm innovation. Because there exists a paucity of studies that qualitatively examine entrepreneurs' stories about the mechanisms we study and their impact on innovation, the qualitative methodological approach was used to examine entrepreneurs' feelings, attitudes, and perceptions (Patton, 2002). Existing empirical studies suggest a positive independent effect of our investigating variables, but we do not yet know enough about their interplay and overall impact on firm innovation.

Interpretative phenomenological analysis (IPA) was found to be the most appropriate method for exploring the personal experiences and perceptions of entrepreneurs (Cope, 2011; Smith et al., 1997; Thompson et al., 1989). IPA attempts to explore real-life motives, largely leans on personal experience, and draws on individuals' perceptions, rather than producing an objective statement (Pietkiewicz & Smith, 2014). Using this method, we may be able to better understand relationships between knowledge breadth, knowledge depth, an entrepreneur's integrative thinking skills, and the overall effect of these factors on firm innovation. Our aim is thus to explore in detail our area of concern and identify essential components of entrepreneur knowledge and integrative thinking in relation to innovation which make them unique, rather than to test predetermined hypotheses.

The study draws on the indicative guidelines for IPA by Smith (2014; 1997). The research questions were designed very broadly with an open inductive approach to understand how entrepreneurs experience our particular phenomena. No predetermined propositions were formed prior to our research.

2.1 Sampling

IPA aims to produce a detailed examination of phenomena rather than to generate a generalizing theory. Nevertheless, the investigation may bring insights into universal mechanisms (Pietkiewicz & Smith, 2014). The method relies on the use of purposeful sampling within a fairly homogenous group, because it involves finding a group of information-rich participants who share significance and relevance for a particular research problem (Greening et al., 1996). Purposeful sampling is constructed to serve our specific need to include entrepreneurs with similar demographic/economic-status profiles, closely related to experiences in innovation, in order to enable a profound examination of our research questions.

IPA studies use small sample sizes because a detailed analysis is time-consuming–the aim is not to generalize but to determine the in-depth perceptions of the participants (Smith, 2015). In theory, a sample of three is recommended because it allows adequate in-depth individual engagement and still showcases similarities and differences between individuals. A larger sample size could lead to overwhelmingly vast amounts of data being generated, which may inhibit production of a sufficiently incisive analysis. Therefore our sample consists of three Slovenian entrepreneurs whom we identified through our personal network.

2.2 Data Collection

The primary methodology used in IPA research is phenomenological semi-structured interviewing. We followed IPA guidelines (Smith, 2015) to attain a first-hand description of investigated domains of the entrepreneurs' experiences. Such interviews allow enough flexibility to provide solid grounds for further detailed examination of unexpected directions and interesting areas that may arise. The interview protocol was loosely structured in advance and began with an opening question without hidden presumptions about the entrepreneurs' personal stories of determinants that can be attributed to their firm innovation, followed by key questions indicating the topics we wanted to discuss. Initial questions were modified to participants' responses by gentle probing (Smith, 2015). When respondents gave intangible answers, we used more-explicit yet still sufficiently vague prompts to move to our addressing areas. Similarly, we strictly avoided evoking a notion of knowledge breadth, knowledge depth, and integrative thinking until the last part of the interview, when we tried to connect their stories with the mentioned mechanisms. We carefully recorded responses provided by participants and loosely funnelled them to the researched topics with minimal probing by asking them more-specific questions. We recorded the interviews with the agreement of all three participants. Their profiles are located in Table 1.

Name	*Profile*
Adam	Adam is a serial entrepreneur, manager, and, recently, a well-known Slovenian business angel. He is a partner in many successful companies and has co-founded one of the biggest online stores in the region. His passion is predicting future trends and exploring the impact of new technologies. Recently he has started to mentor young entrepreneurs.
Ben	Ben is an entrepreneur with a diverse background in programming and philosophy, and can be best described as an evangelist of the regional start-up community. He is a co-founder of the first start-up in Slovenia to acquire venture capital financing. His company raised almost 10 million Euros' worth of investment. He is also a member of a Slovenian business angel fund.
David	David was on the board of directors at one the leading company for direct marketing and e-commerce in Central and Eastern Europe, with over 7000 employees and 300+ million customers. In charge of sales and IT, in his last year he had spent 298 days travelling for business. Later he founded his own start-up to create an imaginative centre where new ideas will arise.

2.3 Data Analysis

Smith (2015) suggests that IPA methodology is flexible, individual, and not prescriptive. Following a set of flexible guidelines, which can be adapted to specific purposes, we used a step-by-step approach to the analysis.

First we transcribed all three interviews, each of which lasted between 70 and 80 minutes. We read all three transcripts several times in order to become more familiar with the content and to identify potential new insights. In each stage of reading, we made additional notes and observations about the content, language, and context. The next stage involved transforming these notes into emerging themes, concise phrases that captured the essential context of the notes. We continued with theme clustering by identifying the connections between emerging themes. These clusters then represented the superordinate themes, which fully capture the entrepreneurs' views of our topic.

Each transcript was searched individually for its own theme clusters without any presumptions. Following identification of convergence and divergence between participants' themes, a final table of superordinate themes was constructed for all three topics under investigation. In the process, certain themes were dropped because they did not fit well within the structure.

Three main superordinate themes emerged for entrepreneur knowledge and eight for integrative thinking. In what follows, we describe each theme and provide evidential interview extracts to support our interpretation and to present entrepreneurs' pertinent perspectives.

2.4 Findings

In the next sections, findings from the IPA analysis are described by categories. We start by demonstrating results for entrepreneur knowledge and conclude with findings regarding entrepreneur thinking.

2.4.1 Entrepreneur knowledge

Extensive knowledge in one field is said to be no longer sufficient. We expect that the more knowledge a person possesses in terms of breadth and depth separately, the more successful, creative, and innovative he/she can be; narrow specialists tend to neglect other points of view and thus are inflexible and hard to work with. On the other hand, if a person possesses only knowledge breadth, his/her skills are insufficient to be a part of strategic process. Therefore, Brown (2005; 2009) postulates that firms need to search for people with balanced knowledge depth and breadth to remain competitive. These two knowledge dimensions can be represented by a so-called T-shaped structure, where a vertical line depicts depth and a horizontal line depicts breadth. Such a balanced person possesses deep knowledge and deep analytical expert thinking skills in his/her field of specialization along with a broad understanding of other disciplines and broad empathy. In this case, depth represents a skill that allows making tangible contributions to the outcome, whereas breadth depicts the capacity and disposition for collaboration across disciplines. Such individuals are curious, open-minded, always eager to learn, and have experience in areas not necessarily directly needed for their jobs. This structure allows them to combine knowledge, i.e., to connect general knowledge, experiences, skills, and hobbies to a problem in the area of their expertise. It enables new perspectives on how to utilize the expert knowledge in many different aspects of life and thus makes entrepreneurs more creative and, ultimately, innovative (Brown & Katz, 2009).

Grant (1996) assumes that narrow-field knowledge itself is not sufficient by exploring mechanisms for effective specialist knowledge integration. He suggests that specialists do not need to know everything from other expertise domains, but communicating their knowledge to other specialists is of particular importance. For such operations, a common knowledge is crucial, because it enhances sharing different aspects of knowledge. Evidentially, there appears to be a solid relationship between an entrepreneur's knowledge and his/her innovativeness, which affects a firm's innovation (Jiao et al., 2014; Marcati et al., 2008). An entrepreneur's knowledge base may improve the likelihood of opportunity recognition and is positively related to innovation radicalness through generated breakthrough insights (Marvel & Lumpkin, 2007). In addition, knowledge breadth has been recognized as a catalyst for successful managerial innovation and innovation performance

(Rodan & Galunic, 2004). In the following sections we review how entrepreneurs actually perceive knowledge in real-life situations.

Participants were asked to discuss all of the determinants that enhance and affect the innovation activity of the firm. They started very broadly and soon narrowed to their personal-level characteristics. The first topic that emerged was personal knowledge. The findings uncover three areas that characterize an entrepreneur's knowledge and its effect on innovation: (1) openness to experiences, (2) knowledge breadth and depth, and (3) learnability and curiosity.

Entrepreneurial openness has gained a great deal of attention recently. Scholars such as Slavec (2014), Ciavarella et al. (2004), and Dean (1999) link it with innovation and performance. In terms of an entrepreneur's openness, all three participants highlighted travel, command of foreign languages, and personal hobbies. These three aspects are prerequisite to gaining new insights which enhance innovation. They enhance idea generation, improve the process of problem solving, and grant easier access to information. As participant David suggests, travelling serves as a foundation for spotting new ideas, enhanced communication, better self-confidence, and a greater understanding: "In this way you can see that the world is not a bogey, that others are not so much more capable than you, you get confidence and lose fear." Similarly, participant Ben argues that personal openness, hobbies and experiences gained through travelling are essential for innovativeness: "The breadth of life experiences significantly increases the likelihood that you will find the optimum solution for whatever is a concrete problem. And it is important to have a personal life just so that your brain remains soft and flexible." In his opinion an entrepreneur's brain is constantly on when faced with an ambitious challenge. It is not rare that one can find a solution to a problem when dealing with a completely different situation. Participant Adam, on the other hand, when discussing the innovation factors, puts significant emphasis on command of foreign languages: "You have to speak different languages to recognize the important actual trends and to acquire information easier."

The next theme that emerged during our data analysis is knowledge in terms of its depth and breadth. Knowledge depth creates a foundation on which innovation can be built (Prabhu et al., 2005). Specifically, depth of experiences contributes to innovation radicalness (Marvel & Lumpkin, 2007). David agrees: "Expertise in a certain area is central for strategic thinking and innovation." The vital role of knowledge depth is also summarized by Ben: "An entrepreneur needs a content to start innovating. You have to know it all to exploit opportunities and to find a gap in a certain area, which could be further optimized and turned into a prosperous business opportunity." Interestingly, Adam stresses the importance of different knowledge dimensions: "To keep your product fresh and competitive, you need to build on your existing expertise and dig deeper into technology, user experience, or even marketing. Similarly, when introducing new products, the knowledge depth in your field is still required; however, in order to construct something completely new, you need to expand your knowledge in various domains to produce something really unique." The need for both knowledge dimensions is best described by David: "I need both knowledge depth and breadth. This is the only way that guarantees new perspectives on how my expertise can be creatively used."

Knowledge in different domains for the purposes of greater innovativeness has been highlighted by several scholars (Bierly & Chakrabarti, 1996; Brown & Katz, 2009; Carlo et al., 2012). Participants highlight the important role of knowledge breadth in enhancing innovation, because combining different disciplines helps uncover innovative solutions. Adam sees knowledge breadth as an important generator of hype and curiosity to start something new and consequently fuel innovation: "You need a horizontal knowledge to be innovative. Not that I am a top expert in all domains, but at least I know which industries are prospective and what is to be expected from them." Ben further outlines the important role of knowledge breadth in innovation: "Knowledge in a certain area may bring an innovative solution to the problem in a completely different area as you try to connect them together. The fact that I taught myself to program in a previous life has a significant impact on my ability to connect different disciplines with programming and search for creative solutions." David adds, "Many times I remember Mr. Japec, who said that his cardiology profession helped him in designing innovative ships."

All three respondents similarly specified knowledge breadth as the most important factor in achieving innovation. Knowledge breadth is vital to understanding what knowledge is missing and how to acquire it. "Breadth helps you to see your lacking skills. And then you go and get this knowledge yourself or find people who have this knowledge," says David. Ben agrees: "I was surrounded by people from whom I could learn from the beginning. And I needed to teach myself how to proactively involve them in my business as consultants." It is important to understand what one can and cannot do, what one knows and what one does not. As Adam says, "The decision who you will hire will affect the end product." Therefore you need to know what you really want to achieve in that particular field in order to develop an innovative product you have in mind. Otherwise the end product may be something completely different from what you had expected. Adam says, "Should we come to an area where I presume someone knows more about it than me, I will be able to let go and participate only as a controller. For that you still have to know something in this field, in order to give the right instructions."

Knowledge breadth is important for solving multi-faceted problems. Ben argues that knowledge breadth enhances communication with employees and offers more-effective control over them to allow for a better and faster innovation process: "Knowledge breadth is important, as you never know what kind of problems you will encounter. It happens that I know how to talk with designers, although I have never worked in this field professionally. But my knowledge in this field helps me hire a better designer and to control his outcomes more effectively, since we speak a common language."

The last theme that emerged is learnability, which is suggested to play a central role in innovation and performance (Cope, 2005; Martin, 2007b; Mi Dahlgaard-Park & Dahlgaard, 2010). In order to be innovative, one needs to constantly learn and nurture one's own curiosity. This is how one broadens and deepens his/her knowledge base, which serves as a foundation on which innovation can be built. Knowledge gained through regular education is never enough. Adam argues that an "entrepreneur needs more and more knowledge each year in order to stay competitive and produce innovative products". Ben adds that "curiosity is a must.

You need to start solving problems not only because they need to be solved, but also because they are interesting. This is how you broaden your horizons." Furthermore, entrepreneurs need to learn how to listen to other people and to recognize things they don't know. Ben claims that "you have to know what and how to absorb and reuse when it matters the most – when searching for an innovative solution". David agrees: "You build your innovative knowledge base with previous experiences, obedience and mistakes along the way."

This deep insight into the entrepreneurs' knowledge builds on the existing theories regarding its role by focusing on three major attributes that seem to be of great essence in practice. It indicates the highly important role knowledge has for entrepreneurs and for their firms. Despite the significance of an entrepreneur's expertise, interviews reveal that it is knowledge breadth that stimulates the problem-solving process and accounts for more-innovative solutions. A firm can be more innovative when an entrepreneur integrates different areas with their own expertise and identifies solutions that are not yet seen. In addition, learnability, openness, and curiosity also are crucial because one's knowledge has to be constantly upgraded and expanded. So in order for a firm to be more innovative, its entrepreneur has to always strive for new experiences. In summary, these comments and themes are suggestive of the strong relationship that knowledge breadth has with knowledge depth and their joint enhanced impact on firm innovation. All things considered, we construct the following proposition:

P1: Breadth of an entrepreneur's knowledge, in terms of general knowledge, experiences, and skills, enhances the effect that the entrepreneur's deep knowledge has on firm innovation.

2.4.2 Entrepreneurs' integrative thinking

The literature describes integrative thinkers as entrepreneurs who do not rely on analytical processes and particularly refuse to accept trade-offs in the form of either/or choices. These entrepreneurs possess the ability to widen the scope of their approach and to see all of the salient aspects of a problem and try to find a way past them by favouring "both/and" thinking in order to create novel solutions (Brown, 2008, p. 87; Brown & Katz, 2009, p. 85). In contrast to Fitzgerald's definition (1945), which in fact creates the foundation for further development of the concept, the new understanding is much more generalized and not exclusive to geniuses (Chamberlin, 1931; Martin, 2007b). Even though there exist leaders who can strengthen their integrative capability through practice and exercise, great integrative thinkers are still rare, mostly due to the anxiety that it causes and to the fact that many leaders choose simplicity and clarity over complexity and ambiguity, which are considered to take much more time and effort (Martin, 2007a). The following paragraphs will serve as an insight into those thinking determinants which entrepreneurs find crucial for being innovative. As it turns out, all of the emerging factors characterize the integrative-thinking process.

The findings of our phenomenological interviewing indicate eight major themes grounded in personal decision-making and thinking processes that affect innovation of the firm: (1)

fast decision-making, (2) 80/20 rule, (3) holistic approach, (4) embracing complexity, (5) comprehensiveness, (6) risk perception, (7) inclusion of others, and (8) future stance.

The interviewees agree that fast decisions in problem solving are crucial for firm innovation. Similarly, the literature tries to understand how to make quality decisions quickly for better performance (Dane & Pratt, 2007; Eisenhardt, 1989; Perlow et al., 2002). It is better to start acting than to try to think of a perfect solution first. Such probing will allow for more-innovative solutions as one deals with the unknowns and puts the elements together in novel ways. David says, "When we opened new markets, we did not make any substantial research of them, no Porter analysis and so on.... We just did it. If we had known all the indexes, then we would have opened half less markets. Sometimes you just need to try." Similarly, Adam agrees, "I make quick decisions and don't waste time with contemplating. As long as you picture your goal in your mind, it doesn't matter which option you will choose. The world will still be spinning and people won't mind." Likewise, it is better to make a mistake than to search for an ideal solution. According to David, "I think it is better to make a mistake on Monday, so you can fix it on Friday, than accept the right decision in two weeks." This is how one becomes involved in the market early enough to learn through mistakes and improve the solution over time.

The second theme to emerge was the 80/20 rule (Koch, 2011; Martin, 2007b). Although the theory of integrative thinking argues that it is worthwhile to put in an additional 80% of effort to reach a solution that is only 20% better, our respondents somewhat objected. All three respondents agreed that the value of time is priceless. "I think it is a waste of time to put 80% more effort in search for only 20% better outcome. I rather use this time to make another product" (David). Indeed, with more time one increases the number of problems one may solve. Ben says, "Today, 60% of the perfect solution can already be enough to be innovative." In his experience, "The problem must only be solved to the point where the next step, whether it is worth to dig in deeper, is confirmed." Correspondingly, one should not focus solely on one solution when one has to get to market as quickly as possible: "Someone else will surely come, who will see a completely different story, and make a better solution with far less effort than I would do" (Adam).

Holistic thinking is another important aspect in achieving innovation (Ambrose & Harris, 2009; Desbarats, 2005). In the participants' experiences, an individual cannot be innovative unless he/she approaches a problem in a rounded fashion. This is the only way in which partial aspects of the problem will not blur the higher meaning and divert the activities. David says, "You have to break a complex problem into pieces, otherwise you won't find the solution. But while working on each piece separately, you still have to think of the whole situation all the time. That enhances innovation for sure, otherwise you just get lost."

Furthermore, complexity evolves an entrepreneur's ability to think innovatively, identify more opportunities, and deal with problems creatively. Indeed, complexity seems important in business (Baggen et al., 2015; Hsieh et al., 2007). Problems are "supposed to be taken as personal challenges. This is how you build up the capacity to innovate," says Ben. Dealing with complex problems should not impose any stress. The search for a creative solution should be a great motivation for entrepreneurs. David says, "You can learn a lot and experience many unconventional solutions. Complex problems give many useful insights that can be used when searching for creative solutions of all the problems to come."

Our respondents strongly emphasized an integrative approach to any problem solving (Ambrose & Harris, 2009; Martin, 2007a). They see it as a path to identifying features of a problem others may miss, and in this way to build an innovative solution. All three entrepreneurs have in common a capacity to search for all the salient data available. That is to say that innovative entrepreneurs have this predisposition. David confirms, "I have many experiences, which help me find the components that may seem hidden. I use these components to make a better decision and ultimately build a better product." When facing a problem, entrepreneurs should first closely examine all its parts from near and far to find something that may be essential for a more-innovative solution and then connect these findings in a non-conventional, non-linear way in order to achieve a greater innovativeness. Adam says, "When I face a certain problem, I try to look at it from different perspectives to find something that is missing and identify all crucial components that may lead to different solutions that are usually overlooked. I also include insights from different people. Then I try to connect these findings in a new, innovative way. This is how firm innovation works." Similarly, Ben says, "First you need to understand the whole story, gather ideas from your co-workers, without any prior established presumption that would inhibit the detection of new facts. Then you connect all the dots and start experimenting. Usually this results in an innovative solution." In addition, in order to get innovative results, Ben mentions the need for "a fast and comprehensive analysis", which in his opinion is extremely rare.

Another important aspect that adds to a more innovative entrepreneur's thinking process is risk perception (Hyrsky & Tuunanen, 1999; Palich & Bagby, 1995). Innovative entrepreneurs are supposed to perceive risk in a different way. According to the participants, there is no such thing as risk and it does not affect their decision-making process. Adam argues, "If you know things well enough, there is no risk involved." Ben adds, "With a great intuition, the risk diminishes." However, they agree that courage is a must and should not be mistaken for risk-taking. David explains, "To find an innovative solution, you do need to go out of the box and have courage into diving into less known areas. Only thus you dare to try new things and grow your creativity and innovativeness by mixing them with accumulated experiences. However, I don't perceive such act as an act of risk-taking."

Entrepreneurs need to have passion for their work. Otherwise, as David states, "they won't find satisfactory and innovative solutions". They need to include other people in their thinking process and search for challenges in discussions with others (Byrne et al., 2009; De Jong & Den Hartog, 2007). That is how a firm can be more innovative as different views are merged together into a solution. According to the interviewees, not many entrepreneurs are open to other people's opinions. That is a true virtue and a distinctive competence. Adam argues, "Entrepreneurs need to have an ear for their employees, friends, and others. Listening to their stories and their insights might give them a completely different view of a certain matter. And then you just need to integrate everything in an innovative solution." In David's words, it is sometimes "difficult to admit you were wrong and others were right, but as soon as you realize that this is the way to a greater innovativeness of a firm, you are on the right path". Moreover, the communication should go in both directions. An innovative and successful entrepreneur will have a passion for sharing his knowledge and for mentoring others. According to Ben, that is one of "the main drivers of entrepreneurship". In other words, giving back to employees gives you more confidence and better recognition. This is how employees will have no fear sharing ideas with an entrepreneur, which "will result in better firm innovation".

A salient topic that emerged is an ultimate orientation towards the future. Greater attention to the future leads to a more effective uncovering of new technologies and an enhanced innovativeness (Martin, 2007b; Yadav et al., 2007). The world has to be seen as full of challenges and changes for the better. This competence is best described by Adam: "To be more innovative, you need to always be in the future with your mind. You need to think how your current solution will affect the future and how you can help build it. You try to do unthinkable, yet necessary in order to be more innovative. You try to predict the future by imagining your product in it and see how well it fits."

Phenomenological interviews offered us deep insight into entrepreneurs' thinking processes. We identified several themes that characterize problem-solving skills important for innovation. These emerging themes also echo important practices of integrative thinking as described by Martin (2007a): consideration of more salient features, multidirectional consideration of causality, visualisation of the whole problem, and refusal to accept unpleasant trade-offs. Because the process has not been investigated thoroughly in the literature, we wanted to gain a close understanding of how an entrepreneur's thinking skills provide more creative and innovative solutions. It turns out that an entrepreneur's thinking is central to problem solving. Different methods and skills of an entrepreneur might result in completely different solutions. In our participants' opinions, these are the characteristics that will grant a higher innovativeness to entrepreneurs and, consequently, better performance and innovativeness to their firms.

We found that the essential characteristics of an entrepreneur's thinking process that enhance problem solving and innovation are also the ones that differentiate an integrative thinker from a conventional thinker: the ability to accept fast decisions, not striving for absolutes, the ability to develop an integrative approach to a problem and keep it in mind while searching for solutions, openness to complex problems, the ability to identify all the invisible components of the problem, constant use of others' opinions, and a different perception of risk-taking and future stance. All these characteristics, according to our observations and our participants' opinions, have a strong impact on their personal innovativeness as well as on overall firm innovation. Consequently, we assert the following proposition:

P2: By using integrative thinking in problem solving, entrepreneurs improve creativity and enhance firm innovation.

3 DISCUSSION AND IMPLICATIONS

This research was intended to improve our understanding of the underlying factors of entrepreneurs' cognitive attributes, to explore how these attributes are related to each other, and to reveal the prevailing personal factors that have a strong effect on firm-level innovation. We used qualitative research methods to understand the feelings, emotions, perceptions, and personality characteristics of entrepreneurs. Specifically, we utilized IPA to explore entrepreneurs' personal experiences about their knowledge and thinking and drew on the individuals' own perceptions. The findings expand the existing view of entrepreneurs' cognitive assets (e.g., Dakhli & De Clercq, 2004; Martin, 2007b) in relation to innovation in order to emphasize a strong link between entrepreneurs and firm-level output.

While supporting the vital role of entrepreneurs in firm innovation, this research supplements the existing theories on knowledge and thinking by suggesting the importance of knowledge breadth for innovation processes. A diversity of experiences acquired by entrepreneurs has been shown to play a vital role in opportunity recognition and firm innovation. These experiences develop an entrepreneur's knowledge breadth, which allows for new perspectives on how to use his/her expertise in different ways. Combining different areas of knowledge makes entrepreneurs more creative and innovative.

Furthermore, innovation is largely dependent on the thinking processes of entrepreneurs. Evidently, in order to achieve innovation and to be better at it, certain thinking patterns emerged which all could be linked to integrative thinking theory (Martin, 2007a). These themes facilitate the innovativeness of an entrepreneur and positively affect overall firm innovation: fast decisions, non-perfectionism, holistic approach, inclination towards complexity, comprehensiveness, collaboration, and future stance.

Our research contributes to the areas of entrepreneurs' characteristics and behaviour and the innovation of SMEs. In sum, our findings correspond to observations in the literature that suggest firm performance and innovation are a reflection of entrepreneur characteristics and behaviours (Baron, 2013; Hmieleski et al., 2015). We provide clearer evidence of the impact entrepreneurs have on their firms by connecting their activities to firm-level outcomes. We analyse and identify the most relevant personal characteristics that contribute to firm-level innovation. This study is among the first to examine knowledge depth and breadth at an entrepreneurial level. So far, the literature encompasses studies of knowledge dimensions mostly at a firm level (e.g., Marvel & Lumpkin, 2007). Using IPA methodology and bridging entrepreneurs' decisions with their SMEs' decisions, we seek to understand entrepreneurs' knowledge dimensions, the mutual interaction of these dimensions, and how they help SMEs to be more innovative. Our findings support previous arguments about the importance of knowledge in innovation (e.g., Farace & Mazzotta, 2015) and complement the understanding of the interplay between its dimensions at the personal level of the entrepreneur. In addition, our results emphasize an important enhancing role that is played by knowledge breadth in terms of general knowledge, experiences, and skills in the relationship between entrepreneur expertise and firm innovation.

Similarly, entrepreneurs' thinking skills that contribute to innovation are explored in detail and linked to the theory of integrative thinking proposed by Martin (2007b). It seems that there exists a certain mindset – attributes of entrepreneurs' thinking processes – that facilitates entrepreneurs' success as well as innovation. In the first stage of this innovative process, the entrepreneur has the capacity to spot less obvious but relevant and salient features of the problem. In the next step, he/she seeks to explore multidirectional and nonlinear relationships between different parts of the problem. In the third step, the entrepreneur creates the relationship model depicting variables from previous steps by using a holistic approach. Finally, the entrepreneur generates an innovative outcome by embracing complexity, considering all parts of the problem, and resolving tensions among opposing ideas.

We have several practical implications for entrepreneurs to facilitate innovation in SMEs. First, the study highlights that entrepreneurs in SMEs have a vital role in fostering innovation because they often play the central decisive role. Based on the interviews, entrepreneur characteristics have a strong impact on firm-level outcomes. Therefore, in order for a firm to perform better or be more innovative, entrepreneurs themselves are a key element of change. Next, our interviews illustrate that entrepreneurs should constantly expand their horizons with travelling, learning foreign languages, and hobbies, because these are prerequisites for easier information acquisition, which can be used in innovative activity. An entrepreneur's openness therefore enhances the innovative idea-generation process and helps gain new insights into the problem area. An innovative entrepreneur should be curious and eager to learn in order to stay competitive and produce innovative solutions. Furthermore, knowledge breadth has been suggested as the vital and most important dimension of knowledge, which entrepreneurs tend to neglect. Entrepreneurs' knowledge breadth increases personal innovativeness and ability to execute and control several activities effectively. Indeed, knowledge breadth is an essential factor in firm innovation because it facilitates an interdisciplinary approach in finding creative solutions. On the other hand, it also reveals gaps in an entrepreneur's knowledge. It helps in human-resource–based decisions, because it grants the capacity to select the right employees for a certain activity and promotes more-effective controlling and monitoring. In addition, entrepreneurs should constantly deepen their expertise to enhance exploitative innovation and identify opportunities in their domains.

Similarly, an entrepreneur's thinking has been shown to largely influence his/her innovative activity and enhance firm innovation. All the themes that emerged in this analysis are strongly connected to the concept of integrative thinking, which is said to enhance a person's innovativeness and ultimately lead to better firm innovation. Evidently, in order to achieve better innovation outputs, an entrepreneur has to possess an ability to make quick decisions. It is better not to invest all the time in searching for a perfect solution to a problem, because this allows more time for experimentation. Moreover, entrepreneurs who utilize integrative thinking have a capability to identify certain components of the problem that many others many not see, which allows them to connect ideas in a way that will boost firm-level innovation. Correspondingly, entrepreneurs who want their firms to be more innovative consider other people's opinions, because these might offer them novel tools to understand different insights and merge them in an innovative solution. Finally, it is important to think about the future. Mentally transferring current problems and possible solutions to the future helps entrepreneurs spot the missing link and identify the right direction, and ultimately leads to more-innovative outcomes for a firm.

4 LIMITATIONS AND FUTURE RESEARCH

There are several limitations to this study. We use qualitative research methods, which typically raise concerns such as subjectivity, sampling, validity, reliability, and statistical generalization (Neergaard & Ulhři, 2007; Stritar & Drnovšek, 2015). In general, with the use of qualitative research our findings cannot be extended to wider populations with the same degree of certainty that quantitative analyses can be (Atieno, 2009). In addition, the generalization is also affected due to the small number of cases used in the study. However, the aim of IPA is to gain rich descriptions of the studied phenomenon, identify its essential components, and explore individuals' perceived insights into different situations, rather than making more-general claims (Pietkiewicz & Smith, 2014). Furthermore, use of small sample sizes and purposeful sampling to find a fairly homogenous sample are suggested in order to attain theoretical generalizability (Smith et al., 1997). Without sufficient experiences in the field of innovation, it would be much more difficult to determine the components that facilitate innovation at an entrepreneurial level. Therefore the individuals analysed in the research were selected on the basis of their own success stories. Such a method would normally lead to a sample selection bias (Heckman, 1977), but the aim of this study is to gain rich insights by understanding a sense of the participants' experience and to compose propositions for further research. Hence future research should focus on additional examination and verification of entrepreneurs' cognitive aspects and their effect on firm innovation. To make results statistically significant, quantitative research methods can be used to test propositions on a large sample without the interference of the researcher's presence that can affect subjects' responses.

Second, IPA suggests using open-ended questions without any hidden presumptions in order for an interview to go into novel areas. As the interview schedule is only suggestive, there is an issue of attained objectivity. Furthermore, probes are allowed to guide a participant and investigation into a certain area of interest. Different techniques may have been used for each individual participant in order to achieve this. In addition, prompts followed from participants' answers may unintentionally affect their subsequent answers. There is a need to conduct such research on a larger scale and to use as uniform an interview schedule as possible.

Third, learning from experience may result in the issue of hindsight bias, which affects individuals' inability to recall their experiences and circumstances accurately (Henriksen & Kaplan, 2003). This simplification of past events describes the tendency for people to overestimate the likelihood of past event occurrences and see them as more predictable (Arkes et al., 1988; Roese & Olson, 1996), and is suggested to be strongly linked to entrepreneurs' recollections of their entrepreneurial experiences (Cassar & Craig, 2009).

Therefore in our analysis we may have overlooked some of the more complex determinants of knowledge and thinking effect on innovation. Further research should be undertaken with a focus on factors of entrepreneur knowledge and thinking which may be affected by hindsight bias.

Fourth, this study does not address an interplay between knowledge dimensions, integrative thinking, and innovation in full detail. There exists a question of their reciprocal effect as well as the strength of their individual effect on innovation. Further studies are needed to identify components that are more essential for innovation than others. To understand this, a measure of integrative thinking and personal knowledge should be constructed. Because integrative thinking is a fresh concept, deriving from experience and observation, the measure would allow for its verification on a large sample of entrepreneurs and explore its significant contribution. Moreover, existing measures of knowledge are based on prior work experience (years in business) and education (education level). In our opinion, these measures do not represent personal knowledge correctly. Rather, a measure should be constructed that would allow the capture of personal level of knowledge according to different fields of expertise.

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MISSING VALUE IMPUTATION USING CONTEMPORARY COMPUTER CAPABILITIES: AN APPLICATION TO FINANCIAL STATEMENTS DATA IN LARGE PANELS

ALEŠ GORIŠEK[1]
MARKO PAHOR[2]

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ABSTRACT: *This paper addresses an evaluation of the methods for automatic item imputation to large datasets with missing data in the setting of financial data often used in economic and business settings. The paper aims to bridge the gap between purely methodological papers concerned with individual imputation techniques with their implementation algorithms and common practices of missing value treatment in social sciences and other research. Historical methods for handling the missing values are rendered obsolete with the rise of cheap computing power. Regardless of the condition of input data, various computer programs and software packages almost always return some results. Despite this fact, item imputation in scientific research should be executed only to reproduce reality, not to create a new one. In the review papers comparing different methods we usually find data on performance of algorithms on artificial datasets. However, on a simulated dataset that replicates a real-life financial database, we show, that algorithms different from the ones that perform best on purely artificial datasets, may perform better.*

Keywords: *missing data, imputation, regression imputation, EMB algorithm, panel data, big data*

JEL Classification: C18, C65

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INTRODUCTION

Methods and procedures concerned with missing values in scientific datasets have been well documented and described. To gain some insight into ad-hoc methods such as complete case analysis[3], available case analysis[4] and single imputation methods like hot

1 University of Ljubljana, Faculty of Economics, PhD candidate, Ljubljana, Slovenia, e-mail: gorisek@gmail.com

2 University of Ljubljana, Faculty of Economics, Ljubljana, Slovenia, e-mail: marko.pahor@ef.uni-lj.si

3 Also known as the Listwise Deletion method. Only cases with complete data are used in analysis.

4 Also known as the Pairwise Deletion method. This method tries to maximize the use of available data in each step of analysis. Even if some data points in a row are missing, but are not needed in the current step, the data that is present is used in the current step of analysis.

deck imputation[5] and mean imputation[6], one could start with Pigott (2001), Tanguma (2000) and Peugh and Enders (2004). These methods are easily implemented, but they require assumptions about the data that rarely hold in practice (Pigott, 2001). Sloppy use of aforementioned techniques can lead to biased or outright wrong results of scientific analysis. Imputation of missing values increases in complexity with the introduction of a regression model[7], stochastic regression model and multiple imputation methods, such as bootstrapped stochastic regression. More complex imputation procedures in general also yield much better imputed values. Thus, the amount of work included, pays dividends. With the wide availability of powerful computers, model based methods like Expectation Maximization (EM), and multiple imputation (MI) methods like Expectation Maximization Bootstrap (EMB)[8] and Approximate Bayesian Bootstrap (ABB) are gaining prominence (Siddique and Belin, 2008). Multiple imputation techniques use bootstrapping to calculate missing value sets with Bayesian or regression imputation (Honaker, King and Blackwell, 2011). Another group are algorithms for autoregressive spectral estimation of lost sample values in discrete-time signals, which can be described with AR and ARMA[9] models (Kazlauskas and Pupeikis, 2014). Genetic Algorithm based, Kernel based, Multi-Layer Perceptron and other Neural Networks based methods have also been evaluated (Andrew and Selamat, 2012).

In the literature, a number of studies exist that compare the effectiveness of different missing value imputation mechanisms in various settings (e.g. Olinsky, Chen and Harlow, 2003; Parwoll and Wagner, 2012; Yesilova, Kaya and Almali, 2011). In these studies authors test different mechanisms of missing data processes, they do however assume some theoretical distribution of the underlying variables, usually the normal distribution. They also assume at least missing at random[10] pattern of missing values. Although these are fair assumptions, corresponding to the standard assumptions of the widely used statistical methods, they do not correspond to empirically observed distributions in social sciences in general and in particular in financial statements data. We show that a purpose-built algorithm on a real-life dataset can outperform the state-of-the-art algorithms that work very well under the assumptions of normal distribution of variables (Allison, 2011). Procedure is tested on a dataset of approximately log-normally distributed variables and a nonrandom pattern of missing data, as the one found in financial reports databases[11].

5 Missing value is imputed with an observed response of similar unit. Historically, the term hot deck originates from the era, when punch cards were used for computer storage. The deck of the cards that was currently being processed was »hot« (Andridge and Little, 2010).

6 Missing value is replaced by the mean of available values.

7 Missing values in one variable are imputed using a regression model based on other variables.

8 EMB algorithm combines EM algorithm with a resampling procedure provided by bootstrapping. A rather mathy derivation of EM algorithm can be found in Dempster, Laird and Rubin (1977). The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and a maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step.

9 AR and ARMA stand for Auto Regressive and Auto Regressive Moving Average, respectively.

10 Missing patterns are explained in the beginning of section 2 of this paper.

11 Special properties of yearly financial reports data are described in subchapter 3.2 of this paper below.

The aim of this paper is not to review all the data imputation techniques and list all possible methods with their assumptions. A good resource for that is Little and Rubin (2014). Missing data imputation is usually a means to an end of a broader research process. The aim of this paper is to show one possible pragmatic approach to research with data that has missing values. The content and the meaning of the data in the encompassing research project are taken into consideration. With the use of the best imputation procedure considering the properties of the data, imputed values are much closer to the true values than with simple or out of the box solutions. Despite the computational complexity of more elaborate techniques, with the right choice of imputation algorithm, much better results and considerable speed gains can be achieved. Speed gains are most notable when using parallel processing capabilities of contemporary computers and other big data technologies.

We compare the performance of the imputation procedures first on an artificially created dataset that follows the conventional normal distribution of variables on two different missing value mechanisms. Then we move to a more realistic case of a large panel dataset of financial statement data for six industries in fifteen countries in ten years from Amadeus[12] database. We use the database to extract the distribution and relations among a set of commonly used variables in economic research. Following these distributions and relations we build a simulated dataset with the same distribution and correlation properties. Finally, we proceed to simulation of different missing value mechanisms on the simulated dataset.

In chapter 2 we continue this paper with a short review of the missing value mechanisms and description of the nature of a practical problem our paper aims to solve. Chapter 3 describes the reasoning behind the derivation and provides the description of the customized two-step imputation algorithm. Chapter 4 describes the real life dataset, used as the basis for our experiments. Chapter 5 is the core of this paper presenting the comparison of performance of various imputation methods. We first check the performance of different imputation methods on the artificial, normally distributed dataset in subchapter 5.1 and then on the simulated dataset that follows the empirically observed distributions and relations in subchapter 5.2. We end the paper with conclusions and suggestion for further research in chapter 6.

1 PROBLEM DESCRIPTION

Missing values are not just blank spaces waiting to be filled with imputed data or somehow removed from the analysis. The pattern of the missing data can contain valuable information. When imputing missing values, one must be most concerned with the so-called missing data mechanism (Eekhout, 2014; Rubin and Little, 2002). Data imputation methods have different assumptions regarding missing data mechanism. If these assumptions do not match the situation with the data, the results of the imputation method may not reflect the real situation. A new reality can be created, which is wrong. Missing data mechanisms can be classified into one of the three categories:

12 Amadeus is a database prepared by Bureau van Dijk. Amadeus contains information on around 21 million companies across Europe.

- Missing completely at random (MCAR)
- Missing at random (MAR)
- Missing not at random (MNAR)

MCAR data are missing totally randomly. One could test for MCAR missing data mechanism using Little's test or some other procedures found in cited literature. Data following MAR pattern are missing at random, conditionally. That is, we know of some variable that influences the amount of missing values and we can control for that variable. MNAR pattern is the most troublesome of all. Missing values are related to some variable for which we cannot control. When deducing the missing value pattern, knowledge of the data and the field of research are of great help.

A typical setting in economic research is to use a panel data structure, e.g. data for a cross-section of companies for several years. If the same cross-section is present in all observed years, we talk about a balanced panel. If companies are entering and leaving the set, we have an unbalanced one. Let us assume that in the final analysis we need k interval variables X_k. These interval variables are analyzed separately for each possible combination of values in l categorical variables C_l. One of the categorical variables C_τ for which $l = \tau$ can also serve as a time series index in panel dataset.

In Amadeus dataset under consideration, observations (companies) were entering and leaving our problem space (the economy). Since we wanted to assess the influence of all available data, we opted for unbalanced panel. Choice of balanced panel would simplify the process, but the analysis would lose a lot of its power due to removal of observations that did not exist at all τ values. As an example, in Table 1 are descriptive statistics on data for four selected industries in Austria.

Table 1: Analysis of the amount of useful data - Amadeus, Austria, selected industries

Dataset	Num. of observations	Valid triplets	Complete cases
Source	217194	510427 (32,5%)	11708 (5,4%)
Imputed where possible	148768	771727 (51,9%)	22119 (14,9%)

Source: Own measurement

Valid data triplet is a tuple of sales, number_of_employees and assets for one company for one year. If any of these three data points is missing, other values are useless in our analysis. Since valid triplets are calculated per year and our dataset has data for 10 years, number of valid triplets must be divided with number of years to be compared to amount of complete cases with data for all years. With "imputed where possible" solution opting for balanced panel (using only 14,9% of all data) would leave us with just a quarter of available data (51,9%).

Another reason for using the unbalanced panel lies in the fact that we are not aware of the missing value mechanism. Choosing a balanced panel on available data could thus introduce bias into the analysis, due to removal of observations that is not random, but follows some existing but uncontrolled for pattern. To check, whether data is valid for certain observation at value τ , we used a control variable X_{τ} , which was complete_year in the case of Amadeus dataset. If the data on X_{τ} is missing or the value of X_{τ} is indicating an invalid set of values for observation n at τ , then the data is not used in further data imputation process. Such subset of data is invalidated. It is prudent to assume, that observations at such singular conditions exhibit different characteristics than under ordinary circumstances, e.g. companies behave differently in years when they are entering or leaving the economy than in years of normal business activities.

Let $D_{[n,(l+k-1)]}$ be the matrix of data observations[13] . D is combined as a block matrix from matrix $C_{[n,l\setminus\{\tau\}]}$ representing the data points with categorical data and matrix $X_{[n,k]}$ representing the data points with interval data.

$$D_{[n,(l+k-1)]} = \left[C_{[n,l\setminus\{\tau\}]} X_{[n,k]} \right]$$

In our case study, data is acquired on the basis of a query to a database, which listed valid values of observed categorical variables C_l as a condition for selection. Thus, a record in the database with a missing value on the observed C_l is automatically excluded from our dataset. This is a clear case where MAR assumption has to be evaluated. MAR is the underlying assumption of many out-of-the-box data imputation algorithms, software packages and programs. If a pattern of missing observations can be suspected, data should be treated accordingly.

Up to this point we know enough about data, that we could brute force execute any out-of-the-box data imputation method listed in the introduction of this paper.

2 CUSTOMIZED MISSING DATA IMPUTATION

In this chapter we describe a custom two-step method for missing data imputation that can be used in contexts of unbalanced panel data, as the one usually found in financial statements databases. We later proceed to show that this method is superior to off-the-shelf methods implemented in contemporary software.

13 n does not represent the number of companies, but rather $\mathit{number\ of\ companies} * \mathit{Card}(\tau)$. In our case τ contains the year of observations and $\mathit{Card}(\tau)$ is the number of all years. Other categorical variables $C_{\Lambda\{\tau\}}$ like country and industry are mere descriptors and do not require special attention.

3 IMPUTATION PREPARATION – MINIMIZING DURATION OF COMPUTATION

Values of X_k interval variables have different covariance matrices depending on the combinations in values of C_I. Because of this our original dataset gets partitioned into $\Pi_{i=1}^{I} Card(C_i)$ [14] independent datasets, some of which may be empty. From the viewpoint of data imputation procedure, computation of independent datasets can be solved in decoupled processes. Such problems are called embarrassingly parallelizable. This fact plays a key role in the employment of big data and other parallel capabilities of IT technology. Usage of parallel computing technology can result in substantial time savings (Wilkinson and Allen, 1999; Fox, Williams and Messina, 2014).

Selection from Amadeus dataset used in this paper contains data for ten (10) years, for six (6) industries in fifteen (15) countries. There are 217194 companies in the dataset. For observation to be valid in a particular year, data is needed for three variables.

The two-step imputation procedure presented below in this article runs a calculation of the mean value of available data for each of three needed variables for each company in the first step. In step two, 10*15*6=900 linear models are estimated. Each of these 217194 * 3 + 900 = 652482 imputation blocks are independent of each other and can be calculated in parallel.

Similar reasoning is employed for multiple imputation methods such as EMB algorithm, also used for comparison following in this article. Well-programmed software packages use the independent partitions in the data, if provided as function call parameters to parallelize the computations.

4 SETTING THE STAGE FOR CUSTOM TWO-STEP IMPUTATION METHOD

With the analysis of the structure and relationships in datasets, taking into account the subject matter of the broader research topic, tailor made data imputation procedures can be prepared. Using the knowledge about the structure of the Amadeus dataset and the expected properties of data on yearly financial reports, following is a derivation of such procedure.

Long dataset where each row contains data for only one observation for one point in time is rewritten to a wide-panel-type of block matrix W. A group of observations where all values of C_I are equal, the only varying categorical column being C_T is rewritten to a wide form as:

$$W_{\left[\frac{n}{\tau},(I-1+k*\tau)\right]} = \left[C_{\left[\frac{n}{\tau},I-1\right]} X_{\left[\frac{n}{\tau},k*\tau\right]} \right]$$

14 $\Pi_{i=1}^{I} Card(C_i)$ is a product of number of elements of all categorical variables.

Each set of values $X_{k,min(\tau)} \cdots X_{k,max(\tau)}$ represents a time series. In the data with imputed values, we want the relationship between variables X_k to stay unbiased. With the use of regression imputation or various multiple regression imputation techniques, we may increase the correlation between X_k variables, thus introducing bias to our research findings. In our example, we want the relationships between data on sales, number_of_employees and assets to remain clean, i.e. imputation of missing values should not make these variables appear more correlated to each other than they are in reality. Even companies from the same industry are organized differently and create value using different mix of resources. That means that even naïve use of Bayesian imputation methods can give us bad results.

Financial statements data of companies are submitted with a well-defined frequency, once a year in our case. The frequency of data sampling is low and transcends seasonal anomalies. The cycles of strong changes in national economic conditions span several decades. It is easy to extract short term trends from the data. In a decade, a zig-zag curve of rapid swings on any of variables from the set X_k for any company is not likely.

The profitability of individual company is in large part dependent on its own, business specific effects (McGahan and Porter, 1997). Thus, we can assume, that existing data about the company is carrying more information about its own missing values, than the data about the rest of the industry in a certain country in a certain year, that we have for other companies. Under such assumptions, mean value imputation is a viable method.

Where for any point in time no data about a variable exists for a company, there is no basis for mean imputation from company's own data. In such case, data about the rest of the industry in a certain country in a certain year can be used in combination with existing data about the company. If such data is present, regression can be used to impute missing data.

As an example of good, context dependent missing value imputation method, below described two-stage procedure is used.

5 CONTEXT DEPENDENT TWO-STEP IMPUTATION METHOD DESCRIPTION

Step 1

If there is enough data present for any partition $C_{\Lambda\{\tau\}}$ in any of the time series from X_k , it makes sense to impute the missing values from this data. Since correlation among time series X_k for individual company is not important in our research, we opt for a simple mean imputation[15]. For all data points where `complete_year` variable is valid, the potential missing value is predicted from neighboring two cells. If no valid values are

15 We are not interested in correlation between time series within one company. That is why attenuation of correlation between variables, which is a consequence of mean value imputation, is not problematic in our case.

available on one side of the time series, a trend deduced from former/latter data points is used. At least two valid data points are needed for such imputation to take place. If there is no data for certain observation in a particular time series, or if there is only one data point, regression imputation described in step 2 is used.

Step 2

From data in the source sample[16], based on our domain specific knowledge, we try to find a variable or combination of variables X_k as regressors in linear model for regression estimation of missing values for particular $X_p \subset X_k$. Financial statement data provide us with several variables X_k that are a superset of X_k. Thus, some are not included in the research model, i.e. are not in the set X_k. These variables are more or less correlated with the variables in the set X_k and can be used as regressors, i.e. inputs into the regression imputation procedure.

$$X_p \subset X_k$$
$$X_p = \overrightarrow{X_r}\vec{\beta} + \vec{\varepsilon}$$

We aim to keep the relationships between variables X_k that are of interest in our final research to be as similar to the true relationships as possible. Using subset of X_k as predictors X_r for one of $X_{j\in k}$ would result in increased correlation between the variables X_k. It is thus desirable that:

$$X_r \cap X_k = \varnothing$$

It is possible, that the linear model from equation $X_p = \vec{X}_r\vec{\beta} + \vec{\varepsilon}$, obtained from regression analysis has insignificant p-values for any β or insignificant F-statistic. Such cases can happen, if there are not enough observations with valid data to successfully estimate a model, if there are nonlinear properties in the data, etc. It is thus necessary, to check for non-significance of coefficients or linear model as a whole and prevent imputation of values for X_p, computed from unreliable regression coefficients[17].

Final data assembly

If a value is present in the original dataset, that value is used. If it is possible to impute the missing values from each observation's own data, mean imputation is used. As a last

16 Another option would be to use the dataset, obtained after execution of imputation in step 1.

17 In our case, exploratory data shows that estimating number_of_employees from costs_of_employees yields strange results if companies with less than 10 employees are taken into account. Since the focus of our broader research problem is on companies with more than 50 employees, we are able to discard observations with number_of_employees value being less than 10. Still, there are combinations of year, industry, country, where no reliable regression model could be estimated.

resort, domain adjusted regression imputation is used, if the obtained linear model has statistically significant coefficients and F-statistic. If none of these options provides a value, data point is left empty (missing value is kept) and is accounted for in subsequent analysis.

6 DATA

The simulations are conducted on two different datasets that are labeled artificial dataset and simulated dataset. Artificial dataset refers to a randomly created dataset where data follow multivariate normal distribution, created purely for testing the results of imputation procedures, accounting for their possible assumptions. This dataset assumes only one period cross-section and simple correlation among variables. Simulated dataset is an artificially created dataset. Distribution and trends in individual time series follow the empirically observed ones found in Amadeus real dataset of financial statements. The missing value mechanism is controlled within the simulation for both datasets.

The missing data mechanism in the observed real financial dataset is unknown; we do know that it is not MCAR due to several reasons. E.g., when observing the percentage of missing values in individual years, more data is missing in earlier years of observations. Thus, data is MAR at best. If missing values are in any way correlated with a value of some variable (e.g.: smaller companies are less likely to report some datum), data is MNAR. If data is MNAR, it violates the basic assumption of some out-of-the-box missing value imputation techniques.

Data about companies (observations) in Amadeus dataset consist of a set of categorical variables C and a set of interval variables X. From Amadeus dataset with financial statements, let us choose set C to consist of country of origin, industry in terms of NACE rev. 2 classification[18], year and complete-year. The element complete-year is telling us, whether the data for a certain company represent the whole year or maybe just some fraction of it. Financial statements for individual companies consist of several tens of more or less correlated data points[19]. For brevity, let us only focus on sales, number_of_employees, costs_of_employees and assets, which are represented in a set of interval variables X.

18 Statistical Classification of Economic Activities in the European Community, Rev. 2 (2008)

19 Before analyzing the empirical data for distribution and relations the data was treated to ensure consistent representation of decimals, missing value identifiers, etc. Data treatment methods are not the focus of this article. Interested readers might want to refer to any introductory text on data analysis. Another important issue in the data preparation process is the decision on detection and treatment of outliers. Readers interested in this topic may refer to Aggarwal (2013) or any other text about outlier analysis. Ignoring or mistreating of outliers can have strong influence on data imputation accuracy (Quintano, Castellano and Rocca, 2010).

Table 2: Correlations between variables from over 3.5M observations of Amadeus data

	Assets	Num. of employees	Costs of employees	Sales
Assets	1.00000	0.95954	0.96216	0.95451
Num. of employees	0.95954	1.00000	0.90290	0.89875
Costs of employees	0.96216	0.90290	1.00000	0.97925
Sales	0.95451	0.89875	0.97925	1.00000

Source: Own measurement

Empirical properties of the real-life dataset

Since we are dealing with panel data, we almost always find clear trends observing particular variable for particular observed subject through time. Variables are also quite strongly correlated. Large companies are in general larger than small companies as measured in all variables: number of employees, costs of employees, assets and sales. Correlations vary depending on industry, country and year. Correlations between variables in the original dataset were calculated using pairwise complete observations[20] approach, to keep as much information about original data as possible. Due to assumptions on which imputation methods are based on, knowing the nature of the dataset is of utmost importance when choosing missing value imputation method.

Due to vast differences in sizes of the companies and the fact that no company has less than zero employees, the distribution of variables is not normal. It is a standard procedure to log the variables, assuming they are log-normally distributed. We find that three variables: sales, costs_of_employees and assets can be approximated by log-normal distribution. It is obvious from the Figure 1 that this assumption is not mathematically exact, but can be applied for the sake of brevity.

7 IMPUTATION METHODS ANALYSIS

We want to guarantee reproducible results, which are not dependent on particular dataset. Thus, we need the capability to control parameters of data and be able to create several different datasets with the same set of parameters. First, we execute a simplified experiment. We create two normally distributed variables, introduce correlation and apply various missing data patterns and imputation techniques. To be able to control the parameters of data distributions, remove noise and control the missing values mechanism, we prepare a simulation procedure, to create a simulated dataset.

20 Available case analysis

8 ARTIFICIAL DATA, TWO VARIABLES, CORRELATION = 0.7

We simulate a series of datasets with two normally distributed random variables, each consisting of 10000 observations and correlation between variables set to 0.7. The simulated datasets are created using random number generator and Cholesky root of desired covariance matrix. On average, the measured correlation in the artificial datasets is 0.699 with a standard deviation of 0.007.

Missing pattern: MCAR

The algorithm is set to randomly remove approximately 20% of data points. After removal some of the cases are missing one and some both variables. The procedure leaves on average 6691.7 complete cases in the dataset, with a standard deviation of just above 18 cases. The average measured correlation of complete cases in the MCAR corrupt data set is 0.700 (s.d. 0.009). On average, the MCAR missing data process does not induce bias in the data, although we do observe an increased variability, probably due to smaller datasets.

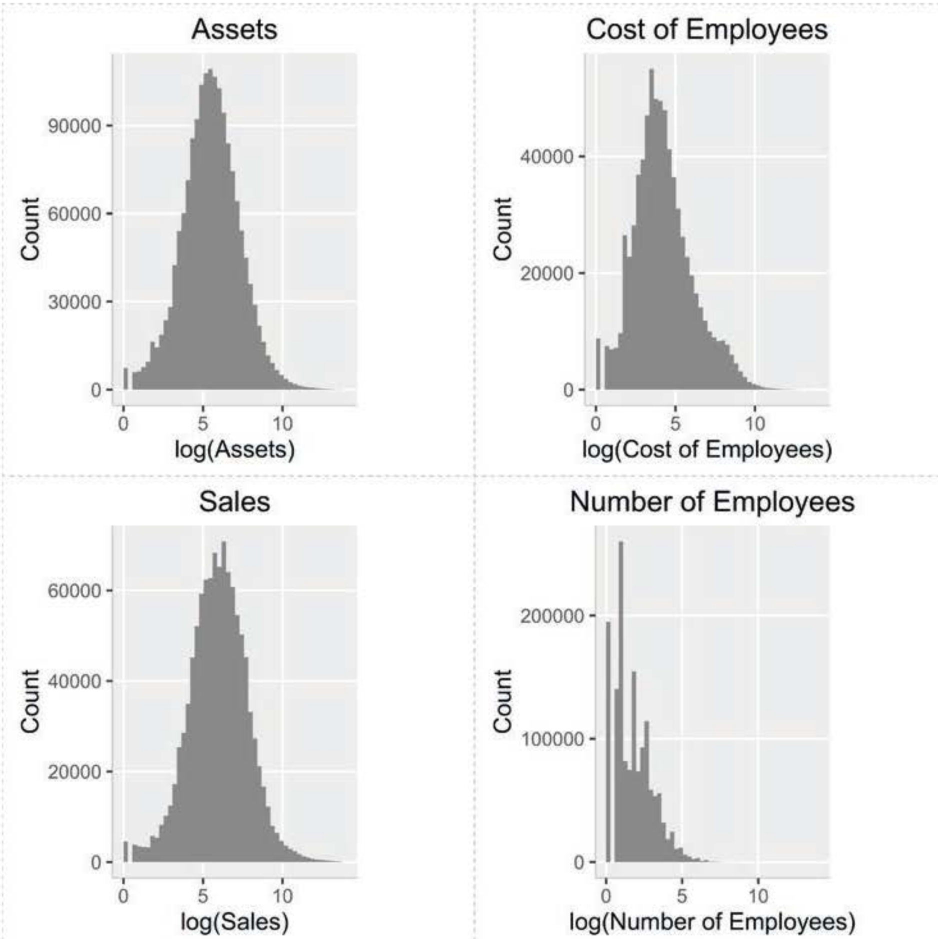
Table 3: Results: MCAR missing pattern, two normally distributed variables

Imputation method	mean(Corr.)	mean(Corr. diff.)	sd(Corr. diff.)	mean(% miss. left)
Mean	0.520	0.179	0.009	0.000
Regression	0.760	- 0.061	0.003	0.032
Amelia (EMB)	0.747	- 0.049	0.003	0.032

Source: Own measurement

The table is showing mean measured correlation between two variables after using each imputation procedure on MCAR pattern in second column. In column showing "mean(Corr. diff.)", the difference between initial correlation (0.7) and measured correlation is shown. Fourth column reports the standard deviation of measured correlation after imputation across several runs of experiment. Last column reports the percentage of values that are left missing.

Figure 1: Distribution of variables in the observed Amadeus dataset

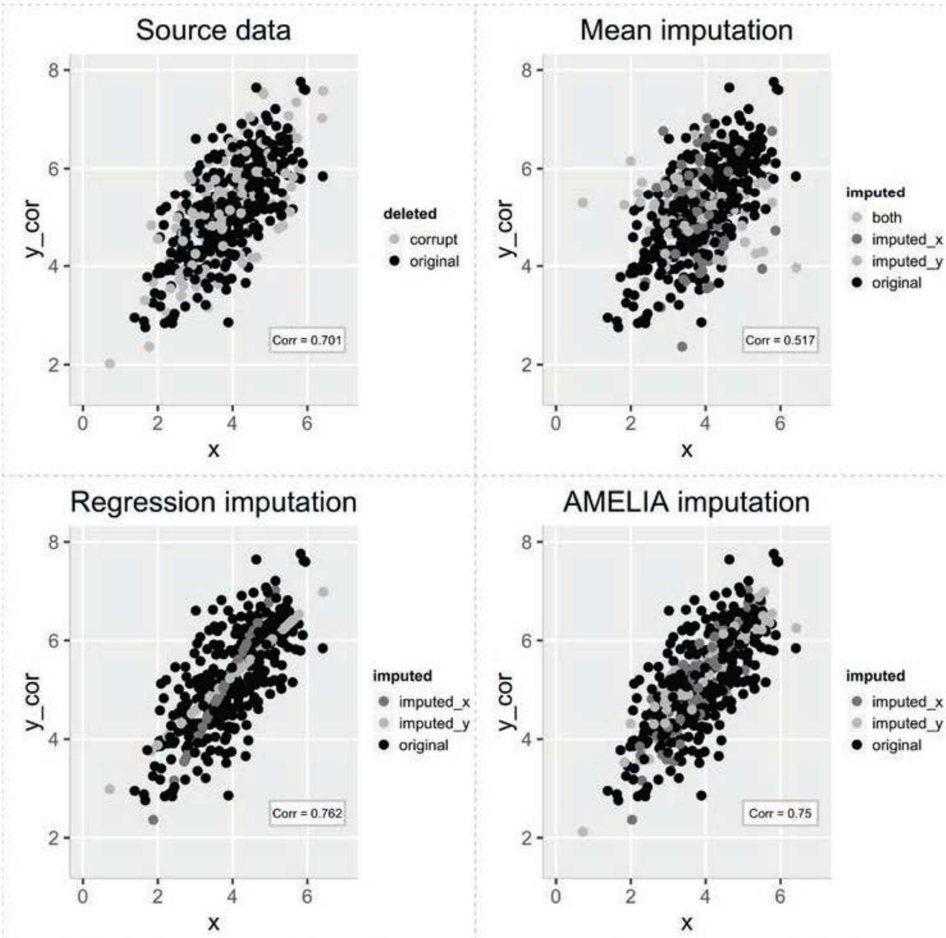


Source: Own measurements and visualization

For the sake of brevity, we can assume that assets, cost of employees and sales are log-normaly distributed. From the picture it is obvious, that this is not exactly true. However, number_of_employees evades the efforts to be molded into log-normal using the same number of bins as for other observed variables. Many companies have very small number of employees and the log function applied to discrete small natural numbers starting with 1 returns values 0, 0.69, 1.10, 1.39, 1.61, etc. Frequencies of these low numbers are high relative to numbers in other observed variables. With low number of bins in a histogram, cumulative distribution function starts to resemble a cumulative distribution function of Binomial distribution, but further analysis of this phenomenon exceeds the scope of this text. To further complicate the matters, companies are reporting rounded numbers. Other mechanisms influencing the distributions may exist, e.g. Amadeus may not include data on all companies from one country, but a certain sample, which may introduce selection bias.

The results of the simulations are presented in Table 3. As expected, mean imputation attenuates the correlation. Both regression imputation and EMB method used in AMELIA II increase the correlation. EMB imputation is showing slightly less biased results, since its initial assumptions are satisfied. Visual representation of results is in Figure 2.

Figure 2: MCAR missing pattern, two normally distributed variables



Source: Own measurements and visualization

The top right picture is showing how mean imputation spreads the imputed points and attenuates the correlation. Increase of correlation as a consequence of regression imputation clearly seen on bottom left picture. The picture on bottom right is produced by EMB algorithm and is less clear, but measured correlation is increased.

Missing pattern: MNAR

Setting the data to simulate the MNAR missing data process is just slightly more complicated. Data points should be missing according to some pattern in the data itself, such that we cannot control for that with another variable. In our case, there is a probability 0.7 for a data point to get corrupted if it matches a condition and zero probability otherwise. The condition is matched if the value in the first column in the row is in bottom 4 deciles of the first column's values. After this procedure we are left with an average of 7125.5 complete cases and a standard deviation of 816.7 cases. Measured correlation of complete cases in the MNAR corrupt data set is on average 0.642 with a standard deviation of 0.011. From the results depicted in Figure 3 we can see that a MNAR process like the one we simulate can introduce some bias to the imputed values, making the correlation between variables presented in Table 4 somewhat weaker.

Table 4: *Results: MNAR missing pattern, two normally distributed variables*

Imputation method	mean(Corr.)	mean(Corr. diff.)	sd(Corr. diff.)	mean(% miss. left)
Mean	0.486	0.212	0.024	0.000
Regression	0.713	- 0.015	0.015	0.096
Amelia (EMB)	0.723	- 0.025	0.018	0.096

Source: Own measurement

The table is showing mean measured correlation between two variables after using each imputation procedure on MNAR pattern in second column. In column showing "mean(Corr. diff.)", the difference between initial correlation (0.7) and measured correlation is shown. Fourth column reports the standard deviation of measured correlation after imputation across several runs of experiment. Last column reports the percentage of values that are left missing.

Again, mean imputation further attenuates the correlation. As in the MCAR case, both the regression imputation and the EMB method used in AMELIA II software increase the correlation. However, in the MNAR case, the regression imputation yields slightly better results than EMB method. We can explain this difference with EMB algorithm's assumption that the missing data pattern is MCAR. This assumption is violated by design of the experiment.

Artificial data, conclusion

Despite the fact, that mean imputation leaves no missing values in the final dataset, significant drop in correlation between the variables can be observed. Both regression and EMB imputation methods yield similar results with the correlation between variables only slightly off target. When the assumptions underlying the EMB method are met, this method proved superior. On the other hand, regression method is proven to be more robust to violations of the MCAR assumption.

9 SIMULATED DATA

Creating simulated dataset from parameters

To simulate correlated random variables resembling real Amadeus dataset given a correlation matrix, we could use the following procedure:

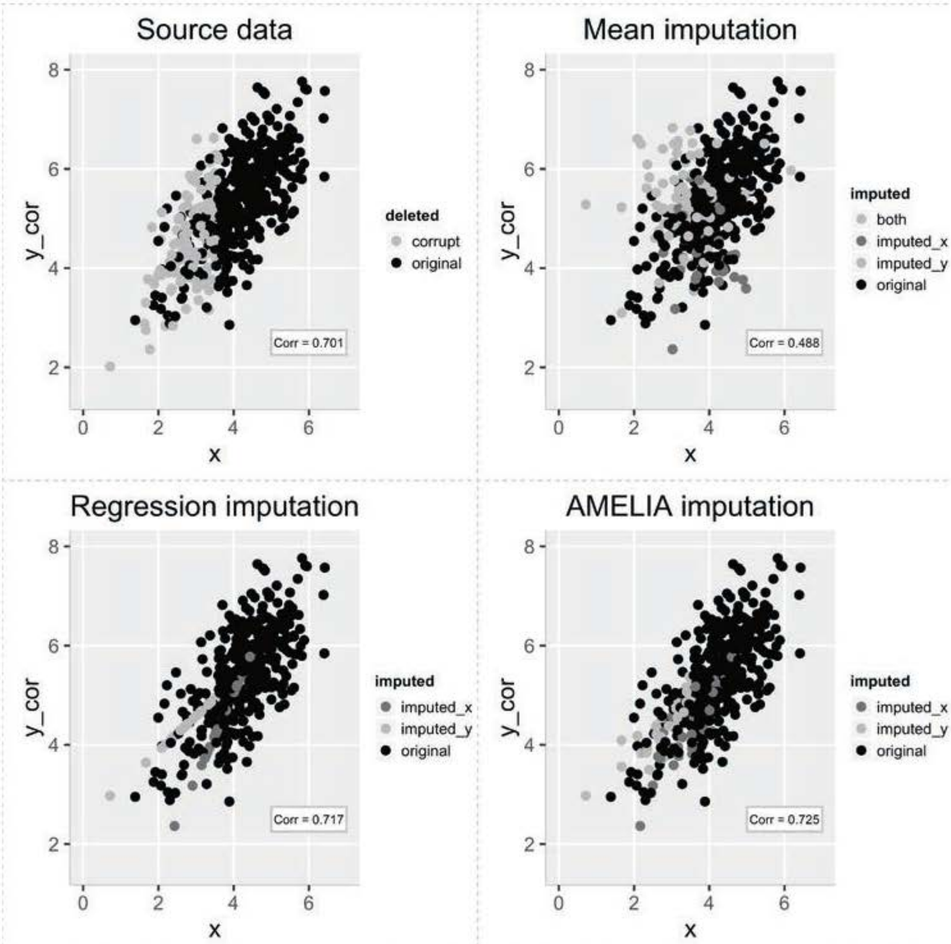
- Calculate Cholesky decomposition of correlation matrix, obtained from Amadeus data for particular year, industry and country
- Generate an $n * k$ matrix of standard normals, Z
- Calculate $X = LZ$ to get correlated normals
- Multiply the columns by σ_i and add μ_i to get correlated nonstandard normal

In the above procedure, n represents the number of observations we want to create. k represents number of variables, X is the final simulated dataset, L is the left Cholesky factor of the decomposition and Z is an individual variable with standard normal distribution. σ_i and μ_i are the parameters of target normal distribution of each variable $i \in \{1...k\}$. This procedure was used to introduce the correlation between the variables in artificial dataset in subchapter 5.1.

Such procedure cannot reproduce trends that are present in original financial statements data. We opted for a less elegant but simpler algorithm, that produces the data retaining the gist of the phenomenon, i.e. somewhat correlated groups of variables with trends:

- Estimate parameters of log-normal distribution of number_of_employees as D_e
- Estimate parameters of log-normal distribution of assets as D_a
- Randomly choose a trend t_e for number_of_employees from uniform distribution, chosen to lie between 0 and 1.5
- Randomly choose a trend t_a for assets from uniform distribution, chosen to lie between 0 and 1.2
- Create a random number $rand_{emp}$ from log-normal distribution with parameters from estimated D_e
- Create a vector of number_of_employees values for one row using $rand_{emp}$ and t_e, number of elements represents the number of years
- Create a random number $rand_{as}$ from log-normal distribution with parameters D_a
- Create a vector of assets values for one row using $rand_{as}$ and t_a
- Correlate assets to number_of_employees
- Find by how much does number_of_employees deviate from sample mean
- Apply the attenuated deviation to assets, we can choose attenuation as parameter
- Create sales which is in linear relationship with number_of_employees and assets, linear coefficients can be chosen as parameters

Figure 3: MNAR missing pattern, two normally distributed variables



Source: Own measurements and visualization

The top left picture shows MNAR missing pattern in the data. The top right picture is showing how mean imputation spreads the imputed points and attenuates the correlation. Increase of correlation as a consequence of regression imputation can be observed seen on bottom left picture. The picture on bottom right is produced by EMB algorithm and is again less clear. However, under MNAR missing pattern its results are more off in comparison to regression imputation as in Figure 2, which depicts imputation with MCAR missing pattern.

- Create costs_of_employees vector that is in linear relationship with number_of_employees, linear coefficient can be chosen
- Introduce some noise, parameters and distribution of noise can be controlled
- Repeat steps from third bullet onwards for as many times as there are rows in the

simulated data set you are creating

Such procedure gives us total control over parameters of the data. With controlled application of missing values using MCAR, MAR and MNAR patterns, we can measure the success rates of imputation methods, depending on all the parameters, with reproducible results.

Simulated data - MAR missing data pattern

Using a real data controlled simulation procedure described in subchapter 5.2.1, we create a series of datasets with 1000 observations of 4 variables in 10 time periods each. To simulate MAR missing pattern, we choose to delete 20% of points in all rows, where first column has a value greater than five. First column is left untouched, so imputation methods can use it. Such criterion results in an average of 2909.1 (s.d. 17.35) deleted data points and 589.2 (s.d. 17.35) complete cases left out of 1000 in initial simulated dataset. First, we would like to know, how closely do the imputed results resemble the ones that were deleted using the missing data process. We thus develop a simple metric to measure the difference between the original and the imputed data that takes account of both: the share of imputed values as well as the quality of imputation. As the metric, we use the sum of differences between the imputed value and the original (deleted value). Results of the simulations are presented in Table 5.

Table 5: Simulated data – MAR missing pattern

	mean(% miss. filled)	mean(% miss. left)	mean(Σ Abs(residuals))	sd(Σ Abs(residuals))
Mean	99.0	1.0	59525	17507
Regression	59.0	41.0	118933	80617
Two step	99.6	0.4	61238	16757
Amelia (EMB)	99.5	0.5	20497329	3338778

Source: Own measurements and calculations

The table is showing in the second column the percentage of data points still missing after each imputation procedure when data has MAR missing pattern. The third column is showing mean sum of absolute residuals (differences between real and imputed value) and the fourth column the standard deviation of absolute residuals after imputation across several runs of experiment.

From the Table 5 we can see that in terms of the share of imputed data, the regression method performs the worst. On average it is only able to replace less than 60 percent of missing data. Mean value imputation replaces 99 percent of missing data. Our two-step method and the EMB method both replace approximately 99.5 percent of missing data. In terms of the quality of imputation, mean imputation and two-step approach yield similarly good results. The two-step method is slightly worse but more consistent. Regression imputation is somewhat worse and much less consistent. EMB imputation proved to be completely inappropriate for this kind of data, as its imputed values deviate greatly from the deleted originals.

Simulated data - MNAR missing data pattern

Again, using a real data controlled simulation procedure described in subchapter 5.2.1, we create a dataset with 1000 observations of 4 variables in 10 time periods. To simulate MNAR missing pattern, we choose to delete 20% of points in all rows, where 23rd column has value greater than some quantile of itself. All columns are corrupt with missing values, so imputation methods are unable to find any pattern in missing value mechanism. Such criterion results in an average of 2975.7 (s.d. 117.9) deleted data points and 589.3 (s.d. 17.49) complete cases left out of 1000 in initial simulated dataset. Results are given in Table 6.

Table 6: Simulated data – MNAR missing pattern

	mean(% miss. filled)	mean(% miss. left)	mean(Σ Abs(residuals))	sd(Σ Abs(residuals))
Mean	98.6	1.4	66359	19999
Regression	59.0	41.0	105235	53220
Two step	99.4	0.6	68005	20471
Amelia (EMB)	99.6	0.4	20504011	3370479

Source: Own measurements and calculations

The table is showing in the second column the percentage of data points still missing after each imputation procedure when data has MNAR missing pattern. The third column is showing mean sum of absolute residuals (differences between real and imputed value) and the fourth column the standard deviation of absolute residuals after imputation across several runs of experiment.

From the Table 6 we can see that in terms of the share of imputed data, once more, the regression method performs worst. On average it is only able to replace less than 60 percent of missing data. Mean value imputation replaces 98.6 percent of missing data. Two-step method replaces 99.4 percent of missing data and the EMB performs best replacing on average 99.6 percent of missing data. In terms of the quality of imputation, mean imputation and two-step approach yield similarly good results. The two-step method is slightly worse but more consistent. EMB imputation manages to impute values to most data points. However, as in the MAR case, the EMB imputation performs worst in terms of imputation quality. Its sum of errors is several orders of magnitude higher than the next best method. Once again, in terms of deviation from true values, mean imputation and two-step imputation perform similarly well. The regression method lags behind both, but beats EMB imputation.

We have shown that in terms of getting missing data close to the "originals", both mean imputation and two-step procedure perform well, regardless of the missing data pattern. However, getting values on average close to the original ones is not yet indicative of whether there will be any bias in the relationships between the variables. As we have seen in the simple simulation in the subchapter 5.1, mean imputation is prone to introducing bias, consistently undershooting the original correlation. Thus, we continue the testing by checking the consistency of a common economics relation, namely a Cobb-Douglas type production function after imputation.

Estimating Cobb-Douglas type production function against imputed data

To test the effects of an imputation method on a well-known estimation problem, we estimate the α, β and A[21] of a Cobb-Douglas type production function.

$$Y = A * L^{\alpha} * K^{\beta}$$

For consistency with real-life datasets the observations in the simulated dataset are allowed to have a value zero. That makes the estimation using least squares regression on logged values impossible. We use an upgraded model that allows for the production function to be consistently estimated even with some values being zero (Battese, 1997):

$$\log(Y) = A + \alpha * \log(L) + \beta * \log(K) + \\ \kappa_1 * Y_0 + \kappa_2 * L_0 + \kappa_3 * K_0$$

$Y0$, $L0$ and $K0$ are dummy variables representing the cases, when Y, L or K have value zero. With such augmentation of the estimated model, we get unbiased results for the three coefficients we are looking for: A, α and β. Obtained values for the estimation on the MAR data are shown in Table 7 and for the MNAR in Table 8.

In our simulation, mean imputation and two-step imputation give the best results in both cases: MAR and MNAR. In both scenarios mean imputation outperforms the two- step procedure in the accuracy of the estimation of regression coefficient. Mean imputation performs somewhat worse in the estimation of the intercept. Complete cases estimation returns estimates that are relatively consistent with non-missing estimation in the slopes but greatly misses the mark for the intercept. Results of the regression imputation and the EMB algorithm are completely biased and as such useless.

21 A represents total factor productivity

Table 7: *Estimated values of Cobb-Douglas production function: MAR*

Data set		A	α	β	$\lvert A-A'\rvert$	$\lvert\alpha-\alpha'\rvert$	$\lvert\beta-\beta'\rvert$
Simulated set	mean	0.222	0.667	0.581	0.000	0.000	0.000
	(sd)	(0.040)	(0.018)	(0.018)	(0.000)	(0.000)	(0.000)
Complete cases	mean	-0.622	0.696	0.618	-0.843	0.030	0.037
	(sd)	(0.077)	(0.016)	(0.023)	(0.097)	(0.007)	(0.010)
Mean imp.	mean	0.223	0.663	0.585	0.002	-0.003	0.003
	(sd)	(0.041)	(0.017)	(0.018)	(0.015)	(0.002)	(0.002)
Regression imp.	mean	-0.487	-0.049	0.099	-0.708	-0.715	-0.482
	(sd)	(0.584)	(0.032)	(0.037)	(0.612)	(0.032)	(0.039)
Two-step imp.	mean	0.222	0.663	0.584	0.000	-0.004	0.003
	(sd)	(0.041)	(0.017)	(0.018)	(0.015)	(0.002)	(0.002)
AMELIA imp.	mean	-0.487	-0.049	0.099	-0.708	-0.715	-0.482
	(sd)	(0.584)	(0.032)	(0.037)	(0.612)	(0.032)	(0.039)

Source: Own measurements and calculations

The table is showing the effects of the choice of missing values imputation method on estimated Cobb-Douglas productivity function coefficients. Pattern of missing values is MAR.

Table 8: *Estimated values of Cobb-Douglas production function: MNAR*

Data set		A	α	β	$\lvert A-A'\rvert$	$\lvert\alpha-\alpha'\rvert$	$\lvert\beta-\beta'\rvert$
Simulated set	mean	0.222	0.667	0.581	0.000	0.000	0.000
	(sd)	(0.040)	(0.018)	(0.018)	(0.000)	(0.000)	(0.000)
Complete cases	mean	-0.622	0.696	0.618	-0.844	0.030	0.037
	(sd)	(0.077)	(0.016)	(0.023)	(0.096)	(0.007)	(0.010)
Mean imp.	mean	0.216	0.665	0.583	-0.006	-0.001	0.001
	(sd)	(0.048)	(0.017)	(0.018)	(0.018)	(0.002)	(0.004)
Regression imp.	mean	-0.621	-0.036	0.084	-0.843	-0.703	-0.497
	(sd)	(0.702)	(0.045)	(0.043)	(0.711)	(0.042)	(0.049)
Two-step imp.	mean	0.217	0.665	0.583	-0.004	-0.002	0.002
	(sd)	(0.051)	(0.017)	(0.019)	(0.019)	(0.002)	(0.004)
AMELIA imp.	mean	-0.621	-0.036	0.084	-0.843	-0.703	-0.497
	(sd)	(0.702)	(0.045)	(0.043)	(0.711)	(0.042)	(0.049)

Source: Own measurements and calculations

The table is showing the effects of the choice of missing values imputation method on estimated Cobb-Douglas productivity function coefficients. Pattern of missing values is MNAR.

Discussion of the results for simulated data

As expected the situation with simulated data is more complex than with the clean artificial dataset. While the off-the-shelf EMB procedure performs quite well in the artificial, normally distributed case, it completely misses the mark for a dataset simulated to resemble the real-life financial reports data. Caution is thus required in the use of such procedures on real life data. The same caution should be applied to some other model-based imputation methods, one of them being the regression imputation that is also presented in this paper.

Simple approaches as complete-case approach introduce considerable bias in the estimates. However, simple mean substitution performs surprisingly well on individual variables from financial reports data. It is beating all other methods in the consistency of model estimations, save for our proposed two-step method. The tailor made two-step method comes close to and partially beats the mean imputation. The main advantage of our proposed method is in the fact that it is able to more than halve the share of non-imputed missing cases on average. This is an achievement comparable to the EMB, but without sacrificing too much of the consistency of results.

10 CONCLUSION AND SUGGESTIONS FOR FURTHER RESEARCH

From the results we can see that the described two-step imputation method yields better results than brute force use of available off-the-shelf algorithms. Assumption that data is missing completely at random or less strict assumption that data is missing at random is often wrong. The brute force use of existing data imputation algorithms can lead to invalid research conclusions.

In order to develop a good data imputation method, suited for particular data and research problem, profound knowledge of the dataset and research topic is of utmost importance. It makes sense to spend time assessing the expedience of different data imputation methods for the problem at hand. We may encounter some sort of consistency vs. efficiency tradeoff, as is the case with the two-step method proposed in this paper or as noted by Kmenta (1997).

The two-step method presented in this article is a tailor made missing value imputation procedure, suited for imputation of missing values into periodic financial reports. The method is far superior to naïve methods with regard to the amount of missing data points restored, while sacrificing small amount of consistency.

An idea for further research is a possible improvement of the two-step method with the use of some multiple imputation method instead of regression in second step. With such a measure, it would be possible to add another bit of stochastic properties to the procedure and perhaps attenuate the already small loss of consistency or further improve the rate of recovered values.

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E/B/R

POVZETKI V SLOVENSKEM JEZIKU

IDENTIFICATION OF THE EQUILIBRIUM EXCHANGE RATE PASS-THROUGH EFFECT IN COINTEGRATED VAR WITH AN APPLICATION TO THE EURO AREA

IDENTIFIKACIJA RAVNOVESNEGA UČINKA PREHAJANJA DEVIZNEGA TEČAJA V KOINTEGRIRANEM VAR MODELU Z APLIKACIJO NA EVRO OBMOČJE

IGOR MASTEN

POVZETEK: *Poznavanje učinka prehajanje sprememb deviznega tečaja v cene je pomembno za nosilce ekonomske politike. Na podlagi članka Johansen (2002) v tem članku izpeljem pogoje* ***za identifikacijo ravnovesnega učinka prehajanja v kointegriranem VAR modelu. Poleg tega specificiram omejitve za testiranje polnega prehajanja v ravnonvesju. Metoda je ponazorjena na*** *podatkih za Evro območje. Rezultati kažejo, da je v odvisnosti od tipa šoka, ki vodi v spremembo deviznega tečaja, učinek prehajanja lahko tako nizek kot visok.*

INNOVATION FOCUSED STRATEGY AND EARNINGS MANAGEMENT

STRATEGIJA OSREDOTOČENA K INOVACIJAM IN KREATIVNO RAČUNOVODSTVO

NATHAN JEPPSON, DAVID SALERNO

POVZETEK: *Študija uporablja tri pristope pri raziskovanju v kolikšni meri podjetja, ki imajo strategije osredotočene k inovacijam uporabljajo kreativno računovodstvo z metodami glajenja prihodkov, realnimi aktivnostmi in časovnimi razmejitvami. Študija je pokazala več rezultatov. Kot prvo, podjetja z inovativno strategijo poročajo o večjem deležu dobička v zadnjem četrtletju, ki kaže večje kreativno računovodstvo. Kot drugo, inovativna podjetja uporabljajo realne aktivnosti v večji meri kot neinovativna podjetja pri kreativnem računovodstvu, kadar uporabljajo benchmarking. Nazadnje, podjetja z inovativnimi strategijami uporabljajo časovne razmejitve v večji meri kot druga podjetja.*

STANDARDS, BEST PRACTICES AND CODES OF ETHICS **IMPACT ON IT SERVICE QUALITY – THE CASE OF** SLOVENIAN IT DEPARTMENTS

VPLIV STANDARDOV, NAJBOLJŠIH PRAKS IN ETIČNIH KODEKSOV NA KAKOVOST IT STORITEV NA PRIMERU SLOVENSKIH SLUŽB ZA INFORMATIKO

DŽANGIR KOLAR, ALEŠ GROZNIK

POVZETEK: *Namen prispevka je raziskati kritične dejavnikov uspeha pri uvajanju standardov, najboljših praks in etičnih kodeksov, katere so njihove koristi po uvedbi ter kako vplivajo na kakovost storitev informacijske tehnologije (IT). Skozi obsežen pregled literature in intervju s strokovnjaki na tem področju smo določili ključne dejavnike. Modeliranje strukturnih enačb (SEM) je bilo uporabljeno na primeru IT oddelkov v velikih slovenskih podjetjih pri preverbi postavljenih hipotez. Študija temelji na 102 izpolnjenih anketah IT menedžerjev v velikih slovenskih podjetjih. Ugotovitve raziskave so potrdile pozitivno korelacijo med navedenimi dejavniki.*

EXPLORING THE INTERPLAY OF AN ENTREPRENEUR'S **THINKING, KNOWLEDGE, AND FIRM-LEVEL INNOVATION**

RAZISKOVANJE MEDSEBOJNEGA DELOVANJA ZNANJA IN NAČINA RAZMIŠLJANJA PODJETNIKA NA INOVATIVNOST PODJETJA

MIHA PREBIL, MATEJA DRNOVŠEK

POVZETEK: *Članek raziskuje znanje in način razmišljanja podjetnika, da bi bolje razumeli njun vpliv na inovativnost njegovega podjetja. Za pridobitev poglobljenega razumevanja kako podjetniki zaznavajo proučevane konstrukte in njihovo obnašanje v podjetjih, uporabimo interpretativno fenomenološko analizo (IPA). Ugotovimo, da podjetnikova širina znanja igra pomembno vlogo pri krepitvi pozitivnega razmerja med njegovo globino znanja in inovativnostjo podjetja. Rezultati pokažejo tudi, da je način podjetnikovega mišljenja pomemben dejavnik v inovacijski aktivnosti. Namreč, podjetnikova zmožnost integrativnega razmišljanja v veliki meri prispeva k inovativnosti podjetja*

MISSING VALUE IMPUTATION USING CONTEMPORARY COMPUTER CAPABILITIES: AN APPLICATION TO FINANCIAL STATEMENTS DATA IN LARGE PANELS

VSTAVLJANJE MANJKAJOČIH VREDNOSTI V PODATKE Z UPORABO SODOBNIH RAČUNALNIŠKIH ZMOŽNOSTI: UPORABA NA VELIKIH PANELIH FINANČNIH IZKAZOV PODJETIJ

ALEŠ GORIŠEK, MARKO PAHOR

POVZETEK: *Članek ocenjuje in primerja metode za avtomatično vstavljanje manjkajočih* ***vrednosti v velike podatkovne množice. Osredotoča se na področje finančnih podatkov,*** *kakršni se pogosto uporabljajo za ekonomske in poslovne analize. Članek želi premostiti vrzel med metodološkimi članki, ki se ukvarjajo s posameznimi metodami vstavljanja manjkajočih podatkov in njihovo algoritemsko implementacijo, ter običajnimi metodami ravnanja z manjkajočimi podatki v družboslovnih vedah in drugih raziskavah. Metode za vstavljanje manjkajočih podatkov, ki so se uporabljale v preteklosti, so zaradi nizke cene in zmogljivosti, ki jo ponujajo sodobni računalniki, postale zastarele. Ne glede na stanje vhodnih podakov različni računalniški programi in programski paketi praktično vedno vrnejo neke rezultate. Kljub temu je potrebno z manjkajočimi podatki ravnati na način, ki preslikava realnost, ne pa ustvarjati nove realnosti. V obstoječih člankih, ki primerjajo uspešnost različnih metod vstavljanja podatkov, so običajno uporabljeni popolnoma umetno kreirani podatki. V tem članku na podatkih, ki simulirajo resnične* ***podatke finančnih izkazov podjetij pokažemo, da obstajajo algoritmi, ki lahko v prak-*** *si delujejo bolje od tistih, ki imajo najboljše rezultate na popolnoma umetnih podatkih.*