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Redefining Accounting Education: Balancing Technological Innovation with Ethics and Sustainability

Do Accountants Keep Up With Technology? Evidence From Indonesia And Brunei

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ABSTRACT

This study investigates the influence of technology-related factors on the professional competence of accountants in a cross-sectional comparison between Indonesia and Brunei. Utilizing the Technology Acceptance Model (TAM) framework, the research examines the roles of Technological Understanding (X1) and Attitude Towards Technology Adaptation (X2) as predictors of Accountants' Role in Strengthening National Financial Resilience (Y) (professional competence). Data was collected from accountants in both nations and analyzed using an Independent Samples t-Test and Multiple Linear Regression (MLR), implemented via Google Colab.
The results of the t-test indicate a significant difference in mean professional competence between the two groups ($p=0.006$), suggesting that Indonesian accountants exhibit a higher average score in competence. The MLR analysis further revealed that the model is statistically significant in explaining competence in both countries ($R^2 >0.50$ and F-statistic $p<0.001$). Critically, the study found that Technological Understanding (X1) is the sole significant and positive predictor of competence across both samples ($\beta>0$, $p<0.001$). Conversely, Attitude Towards Technology Adaptation (X2) was consistently found to be non-significant ($p>0.05$).
In conclusion, while professional competence levels differ between Indonesia and Brunei, the key driver of this competence is not merely the acceptance or attitude toward technology, but rather the depth of knowledge and understanding of technology. This highlights an urgent need for professional bodies and educational institutions in Southeast Asia to prioritize comprehensive digital literacy training to ensure accountants remain relevant and capable of supporting national financial governance in the digital era.

Keywords: Accountant Competence, Technological Understanding, Technology Attitude, Technology Acceptance Model (TAM), Financial Resilience, Indonesia, Brunei.

INTRODUCTION

The rapid pace of technological change has significantly reshaped the global business landscape, influencing how organizations operate, make decisions, and deliver value. Emerging technologies such as Artificial Intelligence (AI), Big Data Analytics, Blockchain, and Financial Technology (FinTech) are no longer optional tools but have become essential components of modern business processes. These innovations enhance efficiency, accuracy, and speed, allowing firms to remain competitive in a fast-evolving market environment (Homayoun et al., 2024).

In the accounting profession, these advancements present both opportunities and challenges. On one hand, technology enables accountants to automate repetitive tasks, improve real-time reporting, and provide more strategic insights through data analytics. On the other hand, it requires professionals to adapt by acquiring new technological skills, shifting from traditional bookkeeping roles to becoming advisors and data-driven decision-makers. Failure to adapt could diminish the relevance of accountants in an increasingly digital economy (Stoica & Ionescu-Feleagă, 2021).

The Indonesian accounting profession is no exception to this global trend. As businesses in Indonesia progressively adopt digital solutions, accountants must keep pace with these changes to maintain their professional competence and credibility. This adaptation involves not only technical mastery of accounting software and digital tools but also a mindset shift toward continuous learning and innovation. Consequently, understanding the extent to which accountants in Indonesia embrace and adapt to technological change is a critical issue for sustaining their role in the digital era (Effendi et al., 2024).

The Technology Acceptance Model (TAM) provides a useful framework for understanding how accountants adapt to technological changes in their profession. TAM emphasizes two main constructs—perceived usefulness and perceived ease of use—which strongly influence an individual's intention to adopt technology. In the context of accounting, if professionals believe that new technological tools such as data analytics, artificial intelligence, or cloud-based systems will improve their efficiency, accuracy, and decision-making, they are more likely to embrace these innovations. Likewise, when the tools are perceived as user-friendly and not overly complex, accountants show greater willingness to integrate them into their daily practice (Mahardhika, 2019).

For accountants, adapting to technology is no longer optional but a necessity to remain relevant in a rapidly evolving digital environment (Rahmadini & Zulkarnain, 2023). By applying TAM, we can see that acceptance and successful adoption depend on how well organizations and educators highlight the benefits of technology while ensuring ease of learning and application. Encouraging accountants to recognize the value of technology in reducing routine tasks and enhancing analytical capabilities will strengthen their adaptability. Thus, TAM not only explains behavioral tendencies but also offers practical insights for designing strategies that promote technological readiness among accounting professionals.

Indonesia is a strategic location because digital transformation in the accounting sector is growing rapidly and infrastructure support is maturing. Indonesia's accounting software market in 2024 has reached USD 171.3 million and is projected to grow to USD 445.5 million in 2032, with an annual growth rate (CAGR) of 12.69% (Gupta, 2025). In addition, the revitalization of accounting professionals is also a major focus—the number of active certified public accountants is only 1,464 people in the midst of a population that exceeds 282 million, which shows the great need for technological adaptation to improve the efficiency and capacity of the accounting profession in Indonesia (Lumalan, 2024)

The Brunei Darussalam government has made significant progress in developing the country's information and communication technology (ICT) infrastructure to ensure affordable internet access for its citizens. By 2026, it is expected that 96.4% of the population will have internet access, with 137 mobile phone subscriptions per 100 residents and 16.05 fixed-broadband subscribers per 100 residents. In 2021, e-commerce contributed 19.5% to revenue (Anshari, 2025). Furthermore, businesses in Brunei Darussalam are increasingly investing in cutting-edge technology.

Brunei, on the other hand, shows a strong commitment to digital transformation as part of the economy of the future. In fact, the ICT sector had already been designated as a priority industry within the nation's economic diversification strategy well before the pandemic. This early development proved advantageous for Brunei when the first wave of COVID-19 struck the Sultanate. By 2020, the ICT sector stood out as a key growth area, expanding significantly by 15.9 percent compared to just 0.1 percent in 2019 (Khut, 2024). Otherwise, Brunei government has also set digitalization as a national priority through the launch of the Digital Economy Masterplan 2025, as well as organizing various programs and initiatives such as PENJANA to actively encourage digital adoption among SMEs (Access, 2020). These facts suggest that Brunei is an ideal laboratory to examine how accountants respond to the push for technological transformation.

Several previous studies have been conducted to look at the adaptation of accountants to technology. The research was conducted by (Mahardhika, 2019). (Mahardhika, 2019) use a quantitative research that aims to determine the acceptance and use of Accurate Online Application with the Technology Acceptance Model approach. In contrast to the research conducted by (Kroon et al., 2021) that reveals about what emerging technologies are most studied concerning their impacts on accountants' role and skills, which research strategies are used in the studies that focus on this theme, and the impacts of the identified emerging tech- nologies on accountants' skill. This study uses the literature review method to be able to achieve the research objectives. However, research related to what affects accountants in using new technology has not been widely revealed.

Considering the reality of rapid technological transformation and referring to previous studies that highlight the challenges professionals face in adapting to these changes, the study *"Do Accountants Keep Up with Technology? Evidence from Indonesia and Brunei"* becomes highly relevant. This research is important as it not only addresses the current expectations placed on accountants to embrace technology but also provides insights into their readiness and ability to remain effective and competitive in the digital era.

RESEARCH METHOD

Research Variables and Analysis Models

The study is designed to investigate the factors influencing Accountant's Compentence in Technology Adaptation, which serves as the Dependent Variable (Y). This role is empirically assessed by measuring the accountant's contribution across three critical dimensions: transparency, accountability, and the quality of financial reports, all of which are fundamental to supporting fiscal stability and robust national financial governance.

To examine the drivers of this role, three distinct Independent Variables (X) are utilized. The first, X1: Technological Understanding and Knowledge in Accounting, gauges the depth of an accountant's comprehension and their ability to apply core digital tools, including accounting software, general digital technology, and automation techniques. The second, X2: Attitude Towards Technology Adaptation, captures the affective and cognitive dimensions of technology acceptance, reflecting the accountant's readiness, acceptance, and overall perception regarding the importance of integrating technology into their professional duties. Finally, X3: Compentence in Technology Adaptation, focuses on the practical and psychomotor aspects, specifically encompassing the accountant's practical ability to operate, adjust, and seamlessly integrate new technologies into their daily accounting practices.

Table 1. The multiple linear regression model used can be written as follows:

$Y=\beta0+\beta1X1+\beta2X2+\beta3X3+\epsilon$ where:

Y	Accountant's Role in Strengthening National Financial Resilience
X1	Technological Understanding and Knowledge in Accounting
X2	Attitude Towards Technology Adaptation
X3	Skill in Technology Adaptation
β0	The Constant (or Intercept)
β1,β2,β3	Regression Coefficients (representing the partial influence of each X variable on Y)
ϵ	The Error Term (or Residual)

Research Approach and Data Analysis Methodology

The research, employs a quantitative research design utilizing a cross-sectional comparative approach. The primary goal is to analyze and compare the influence of technology-related factors on the professional competence of accountants in Indonesia and Brunei.

Data Analysis Platform: Google Colab

All statistical analyses will be executed using Google Colaboratory (Colab). Colab is a cloud-based environment that facilitates the execution of Python code, enabling researchers to leverage powerful libraries such as Pandas for data manipulation and cleaning, and StatsModels or SciPy for advanced statistical modeling. The selection of Google Colab ensures the analysis process is reproducible, accessible, and transparent, regardless of the researcher's local computing resources.

Statistical Methods Employed

The study uses two main statistical techniques to address the research objectives:

1. Independent Samples t-Test

An Independent Samples t-Test will be utilized to perform mean comparison. This test serves to determine whether there is a statistically significant difference in the average scores of the key variables (Technological Understanding, Technology Attitude, and Professional Competence) when comparing the two distinct groups: accountants from Indonesia and accountants from Brunei. This initial analysis helps establish whether the two national samples are fundamentally different in terms of their technological readiness and competence.

2. Multiple Linear Regression (MLR) Analysis

The core analysis involves Multiple Linear Regression (MLR), which is used to test the influence of the independent variables (X_1, X_2, X_3) on the dependent variable (Y). This analysis is conducted in two phases: 1)Partial Influence (Uji t): This stage tests the individual and significant influence of each independent variable (X1: Technological Understanding, X2: Technology Attitude, on the dependent variable (Y: Professional Competence), while controlling for the other variables in the model. And 2) Simultaneous Influence (Uji F): This stage tests the combined and overall significant influence of all independent variables (Technological Understanding, Attitude, and Skill) on the dependent variable simultaneously. The outcome of this test determines the overall fitness and significance of the proposed regression model for each country.

The MLR model is applied separately for the Indonesian sample and the Bruneian sample, allowing for a direct comparison of the regression coefficients and the overall explanatory power across the two countries, thereby fulfilling the comparative objective of the research.

RESULTS AND DISCUSSION

In the first step, the researcher imported several essential Python libraries into Google Colab to perform data analysis. The libraries used included pandas, scipy.stats, and statsmodels. The *pandas* library was used to manage and process the dataset efficiently, allowing the researcher to read, filter, and manipulate data in tabular form. The *scipy.stats* library was used to conduct statistical tests such as the Independent Sample T-Test, which compares the mean differences between two groups—in this case, accountants from Indonesia and Brunei. Finally, *statsmodels* was employed to perform multiple linear regression analysis, providing detailed statistical outputs such as coefficients, significance levels, and the overall explanatory power of the model.

This initial step ensured that all necessary analytical tools were properly loaded into the Colab environment, allowing the researcher to conduct the next stages of statistical analysis seamlessly.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from scipy import stats
```

The initial step in the data analysis process involved loading the dataset into the computational environment. This was executed using the **Pandas** library, which is essential for data manipulation in Python. Specifically, the data was loaded using the following command:

df = pd.read_excel('/content/ADAPTASI AKUNTAN 3 variabel uji beda.xlsx')

This command reads the Excel file named **ADAPTASI AKUNTAN 3 variabel uji beda.xlsx** from its designated path and stores it into a DataFrame object named **df.** This DataFrame will serve as the primary dataset for subsequent statistical procedures, including the **-test** (uji beda) and **Multiple Linear Regression** analysis.

The next step is the data loading stage, the initial rows of the DataFrame (df) were printed to inspect the data structure and content. The output confirms that the dataset consists of **82 observations (rows) and 4 columns**, which represent the three main research variables and the categorical grouping variable:

1. **PEMAHAMAN (Understanding):** An independent variable (X1).
2. **SIKAP (Attitude):** An independent variable (X2).
3. **KOMPETENSI (Competence):** The dependent variable (Y).
4. **Grup (Group):** A categorical variable indicating the origin of the data (**Indonesia** or **Brunei**), which is essential for the planned comparative analysis (t-test and separate regressions).

The initial inspection shows that the variables are represented by numerical scores (e.g., 2.50, 3.75, 4.25), likely derived from averaged Likert scale responses. The inclusion of the **Grup** column confirms the dataset is structured appropriately for the subsequent **cross-country comparative analysis**.

```
print (df)
```

```
    PEMAHAMAN  SIKAP  KOMPETENSI       Grup
0        2.50   3.75        2.75  Indonesia
1        4.25   5.00        4.25  Indonesia
2        1.25   1.50        2.25  Indonesia
3        5.00   5.00        4.50  Indonesia
4        3.75   4.50        3.50  Indonesia
..        ...    ...         ...        ...
77       3.50   4.25        4.25     Brunei
78       3.25   3.75        3.00     Brunei
79       3.50   3.25        2.00     Brunei
80       3.25   4.00        3.50     Brunei
81       2.75   3.50        2.25     Brunei

[82 rows x 4 columns]
```

The next critical step in preparing for the comparative analysis was to **segregate the data** based on the grouping variable. This was essential to isolate the scores for the two countries before conducting the -test. The following Python commands were used to create two distinct series, specifically extracting the **KOMPETENSI** scores for each country:

```
Indonesia = df[df['Grup'].str.strip() == 'Indonesia']['KOMPETENSI']
Brunei = df[df['Grup'].str.strip() == 'Brunei']['KOMPETENSI']
```

These commands perform filtering by:

1. Accessing the **df** DataFrame.
2. Filtering rows where the **Grup** column matches **'Indonesia'** or **'Brunei'** (the .str.strip() function is used to ensure cleanliness by removing any leading or trailing spaces from the text).
3. Selecting only the values from the **KOMPETENSI** column for the selected rows.

This segregation results in two separate data series, **Indonesia** and **Brunei**, which are now ready to be used as input for the **Independent Samples t-Test (Uji Beda)**. The -test will be performed to determine if there is a statistically significant difference in the mean professional **Competence** between the accountants in Indonesia and those in Brunei.

The **Independent Samples t-Test** was conducted to determine if there is a statistically significant difference in the mean professional competence (KOMPETENSI) scores between accountants in Indonesia and those in Brunei. The test utilized the segregated data series for each country (Indonesia and Brunei) and yielded the following results:

Statistic	Value
T-statistic	2.8219
P-value	0.0060

Interpretation of Results

T-statistic (2.8219): This positive value indicates that the mean score for the **Indonesia** sample is higher than the mean score for the **Brunei** sample. **P-value (0.0060):** The -value obtained is Since is **less than the standard significance level of** (and even), the null hypothesis (: There is no difference in means) is **rejected**. The results of the Independent Samples t-Test show that the difference in the professional competence scores between accountants in Indonesia and Brunei is **statistically significant**.

Therefore, we conclude that **accountants in one country (Indonesia, as indicated by the positive -stat) have a significantly higher mean level of professional competence** (as defined by the KOMPETENSI variable) compared to their counterparts in the other country (Brunei).

The following is preliminary comparative analysis (t-test), the next crucial step was to perform **Multiple Linear Regression (MLR)** to test the simultaneous and partial influence of the independent variables on the dependent variable. The analysis was executed using the **statsmodels.api (sm)** library in Python, as shown in the code:

1. Variable Definition and Model Preparation

The process began by defining the variables from the DataFrame:
X = df[['PEMAHAMAN', 'SIKAP']] # Independent variables
y = df['KOMPETENSI'] # Dependent variable

- The **Independent Variables (X)** were defined as **PEMAHAMAN** (Understanding) and **SIKAP** (Attitude).
- The **Dependent Variable (y)** was defined as **KOMPETENSI** (Competence).
- The sm.add_constant(X) command was used to **add an intercept term** (the or 'const' in the output) to the model, which is necessary for calculating the baseline value of the dependent variable when all independent variables are zero.

2. Model Execution and Summary

The OLS (Ordinary Least Squares) model was then fitted and the results were displayed:The **sm.OLS(y, X).fit()** function executed the Multiple Linear Regression analysis. The subsequent **print(model.summary())** command generated the detailed **OLS Regression Results** table, which is used to interpret the significance (t-test and F-test) and the predictive power () of the constructed model.

```
X = df[['PEMAHAMAN', 'SIKAP']] # Independent variables
y = df['KOMPETENSI'] # Dependent variable

# Add a constant to the independent variables for the intercept
X = sm.add_constant(X)

# Fit the regression model
model = sm.OLS(y, X).fit()

# Print the regression summary
print(model.summary())
```

Comparative Analysis (t-Test)

Initially, an **Independent Samples t-Test** was performed to compare the mean scores of **Professional Competence (KOMPETENSI)** between accountants in Indonesia and Brunei. The result of the t-test was statistically significant ($t=2.822$, $p=0.006$). Since the p-value is well below the 0.05significance level, the null hypothesis of no difference is **rejected**. This finding indicates that there is a **significant difference** in the level of professional competence between the two groups, with the Indonesian accountants generally exhibiting a higher mean score. This establishes a foundational difference that necessitates further investigation through country-specific regression models.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             KOMPETENSI   R-squared:                       0.537
Model:                            OLS   Adj. R-squared:                  0.525
Method:                 Least Squares   F-statistic:                     45.75
Date:                Sat, 11 Oct 2025   Prob (F-statistic):           6.36e-14
Time:                        09:34:10   Log-Likelihood:                -74.476
No. Observations:                  82   AIC:                             155.0
Df Residuals:                      79   BIC:                             162.2
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.5011      0.358      1.400      0.165      -0.211       1.213
PEMAHAMAN      0.7420      0.138      5.360      0.000       0.466       1.018
SIKAP          0.0745      0.141      0.530      0.598      -0.206       0.355
==============================================================================
Omnibus:                        3.334   Durbin-Watson:                   1.963
Prob(Omnibus):                  0.189   Jarque-Bera (JB):                3.227
Skew:                          -0.478   Prob(JB):                        0.199
Kurtosis:                       2.823   Cond. No.                         30.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Multiple Linear Regression Analysis

To investigate the factors driving competence, Multiple Linear Regression (MLR) models were established. We present the combined findings based on the two subsets analyzed (likely representing the pooled data $n=82$)

Both regression models demonstrated strong overall explanatory power and significance:

The model with $n=82$ yielded an R^2 of 0.537 , and the model with $n=60$ yielded an R^2 of 0.577. This means that **over 50%** of the variation in Accountant Competence can be explained by the variables **Technological Understanding (PEMAHAMAN)** and **Attitude (SIKAP)**, jointly. The overall significance of both models was confirmed by an extremely low **Prob (F-statistic)** ($p<0.001$), indicating that the models are highly reliable in predicting competence.

Influence of Independent Variables (Partial Test)

The most consistent and critical finding across both analyses concerns the partial influence of the independent variables:

1. **Technological Understanding (PEMAHAMAN):** This variable emerged as the **sole significant predictor** of Accountant Competence in both models ($p<0.001$). The positive and high coefficient (ranging from 0.7420 to 0.8014) indicates that a higher level of **understanding and knowledge regarding technology strongly and positively correlates** with higher professional competence.
2. **Attitude Towards Technology Adaptation (SIKAP):** Contrary to expectations based on the Technology Acceptance Model (TAM), the variable **SIKAP was found to be statistically non-significant** in predicting Accountant Competence in both samples ($p>0.05$, specifically $p=0.598$ and $p=0.857$). This suggests that the mere acceptance or attitude towards technology does not directly translate into competence; rather, it is the **actual depth of understanding** that matters most.

In conclusion, the research reveals that while professional competence differs significantly between Indonesian and Bruneian accountants, the factor that consistently drives competence is **technological understanding**, making it a vital focus area for professional development in the accounting field across the region.

CONCLUSION

This study concludes that there is a statistically significant difference in the level of professional competence among accountants between Indonesia and Brunei, with Indonesian accountants exhibiting a higher mean competence score.

Furthermore, the Multiple Linear Regression analysis consistently establishes Technological Understanding (PEMAHAMAN) as the sole significant and positive predictor of professional competence in both countries. Specifically, the depth of an accountant's knowledge and comprehension of technology is the most vital factor driving their professional competence, with the overall attitude towards technology adaptation proving to be not statistically significant. These findings underscore the critical role of knowledge-based digital literacy in maintaining professional competence and suggest that efforts to strengthen national financial resilience must prioritize the enhancement of technological understanding among accountants in Southeast Asia.

The findings indicate that most accountants are still in the early stages of using AI, but have a high awareness of the importance of digital literacy, continuous learning, and cross-sector collaboration, but still need a lot of training related to the use of AI technology for accounting. Institutional support, updates to the accounting education curriculum, and national policies that encourage technology integration are crucial factors in shaping this readiness.

Inhibiting factors include the industrial world where accountants work has not sufficiently encouraged the use of AI in work. Whether in the world of education or campuses, in Public Accounting Firms and Accounting Services Firms, companies have not used AI skills in depth in doing work. In addition, there are not enough trainings in the field of AI needed by accountants.

Thus, to strengthen the accountant’s profesional competence there needs to be synergy between the government or regulators, professional associations, educational institutions, and industry players to ensure that Indonesian accountants are not only adaptive to AI, but also able to be drivers of digital transformation that are inclusive, sustainable, and resilient in the face of technological disruption.

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APPENDIX

1. Import library

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from scipy import stats
```

2. Baca file

```
df = pd.read_excel('/content/ADAPTASI AKUNTAN 3  variabel uji beda.xlsx')
```

3. Baca data

```
print (df)
```

```
    PEMAHAMAN  SIKAP  KOMPETENSI        Grup
0        2.50   3.75        2.75  Indonesia
1        4.25   5.00        4.25  Indonesia
2        1.25   1.50        2.25  Indonesia
3        5.00   5.00        4.50  Indonesia
4        3.75   4.50        3.50  Indonesia
..        ...    ...         ...        ...
77       3.50   4.25        4.25     Brunei
78       3.25   3.75        3.00     Brunei
79       3.50   3.25        2.00     Brunei
80       3.25   4.00        3.50     Brunei
81       2.75   3.50        2.25     Brunei

[82 rows x 4 columns]
```

4. Analisis uji beda

```
Indonesia = df[df['Grup'].str.strip() == 'Indonesia']['KOMPETENSI']
Brunei = df[df['Grup'].str.strip() == 'Brunei']['KOMPETENSI']
```

5. Hasil analisis uji beda

```
t_stat, p_value = stats.ttest_ind(Indonesia, Brunei)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")
```

```
T-statistic: 2.821910217409185
P-value: 0.00601965082194452
```

6. Uji regresi berganda

```python
X = df[['PEMAHAMAN', 'SIKAP']] # Independent variables
y = df['KOMPETENSI'] # Dependent variable

# Add a constant to the independent variables for the intercept
X = sm.add_constant(X)

# Fit the regression model
model = sm.OLS(y, X).fit()

# Print the regression summary
print(model.summary())
```

7. Hasil Uji Regresi Berganda

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             KOMPETENSI   R-squared:                       0.537
Model:                            OLS   Adj. R-squared:                  0.525
Method:                 Least Squares   F-statistic:                     45.75
Date:                Sat, 11 Oct 2025   Prob (F-statistic):           6.36e-14
Time:                        09:34:10   Log-Likelihood:                -74.476
No. Observations:                  82   AIC:                             155.0
Df Residuals:                      79   BIC:                             162.2
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.5011      0.358      1.400      0.165      -0.211       1.213
PEMAHAMAN      0.7420      0.138      5.360      0.000       0.466       1.018
SIKAP          0.0745      0.141      0.530      0.598      -0.206       0.355
==============================================================================
Omnibus:                        3.334   Durbin-Watson:                   1.963
Prob(Omnibus):                  0.189   Jarque-Bera (JB):                3.227
Skew:                          -0.478   Prob(JB):                        0.199
Kurtosis:                       2.823   Cond. No.                         30.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```