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Factors Affecting the Forecasting Ability of Implied Correlation in Currency Options

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ABSTRACT

Little research has been done into implied correlations, and the small literature grows even smaller when referring to currency options. The existing literature has established that implied correlation is a good if not the best forecaster of future realized correlation, and that this ability to forecast is not necessarily universal. This paper will establish that the forecasting ability of implied correlations in currency options varies across currency pairs, thus proving that not all implied correlations are created equal. Using two different proxies for the quality of the forecaster, the paper attempts to explain which characteristics of an option on a currency pair affect the variation in forecasting ability.

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I. Introduction

The literature on implied correlations in the FX options space is certainly limited. It establishes that implied correlation contains information on future realized correlation, and even goes as far to claim that not all implied correlations contain the same amount of information. My thesis can be broken down into two parts, firstly that the implied correlations backed out of options on different currency pairs contains a varying amount of information on future realized correlation, and secondly that the variation in the forecasting coefficient can be explained.

Before I go further into describing the two parts of my thesis, it is important to briefly establish what an implied correlation is. While I will explain and show how to derive implied correlations in a later section, an intuitive understanding is important at this point. Currencies are a zero sum game, as when one buys a currency they also sell another. For example, buying the EURUSD means buying the Euro and selling the Dollar. The change in the demand for the two currencies would have an effect on the value of any other currency pair that includes one of them, such as EURJPY or USDJPY. These changes in spot prices would result in a realized correlation between the different pairings. Implied correlation can be derived from option prices. It is a direct input in many exotic options, such as any basket option or a barrier option in which the payout and the barrier are structured in different currency pairs. However, implied correlation can also, and for the case of this paper, is derived from vanilla options. Think of currencies A B and C, that are traded as A/C, B/C, and A/B. Now, recall that the trading of A/C and B/C would affect the price of A/B, due to the actual change in demand for currencies A, B and C. Thus, if we can observe the volatility of A/C and B/C it stands that we would know something about the volatility of A/B. Yet, simply knowing the levels of A/C and B/C would not be enough to inform us on the level of A/B, for the relationship exists due to their being an effect on A/B when A/C or B/C trades. This effect is the correlation. It is when the market buys A/C, how much of an effect does the decreased demand of B have on the price of B/C as opposed to other pairs. Therefore, the implied volatility on A/B provides insight into the levels of implied volatility for A/C and B/C as well as some description on how A/C and B/C interact, or their correlation. Again, I will further explain and properly define implied correlation in a later section, but this intuitive understanding is important.

An earlier paper, Walter and Lopez (2000), which I rely heavily on for insight and methods, looks at two different currency trios, and finds that for one implied correlation is the best forecaster of future realized correlation just as the previous literature would indicate, but the other trio's implied correlation is not a good forecaster. The first part of my thesis, looks to further prove that not all implied correlations are created equal, and that the forecasting ability of implied correlations varies dramatically. While, the Walter and Lopez paper would indicate that this should be true, they do not go far as to definitively prove it. Additionally, their options data is far older than mine, and option prices from those times reflect much less sophisticated pricing models from firms. Thus, I hope to clear all doubts that across a broad range of currency pairs, the forecasting ability of implied correlations varies.

If my hypothesis that there will be variation in forecasting ability is correct, I will next attempt to explain the variation. The paper is looking at why certain implied correlations are good at predicting future realized correlations. Thus, the characteristics of both the implied and realized correlation will be possible explanatory variables. As will characteristics of the implied volatility from which implied correlations are derived. Finally, the liquidity of these options should also be important in explaining the variation. My methodology section will further explain the various proxies I used to capture the variation as well as the explanatory variables.

II. Literature Review

There has been limited research into the forecasting ability of implied correlations derived from options prices. This literature is even smaller when restricted to a focus on currency options. The literature relies heavily on the insight and techniques used in much larger literature examining the forecasting relationship between implied and realized volatility.

The discussion of whether implied volatility, due to its forward looking nature, is a good predictor of future realized volatility is split. On one extreme is the belief that option prices, which when priced by the Black Scholes model, reflect implied volatility, have no forecasting or correlation with future realized volatility. Canina and Figlewski (1993) find that in S&P 100 indexes, implied volatility has less informational value than recently observed volatility. Although most of the literature would agree that implied volatility is biased, it is believed to still be of use as a forecaster, Canina and Figlewski (1993) claim that implied volatility holds no information or use in forecasting future realized volatility. Two of the more interesting explanations the paper gives for their results is that the option price differs from true expected future volatility due to a skew demand and that the implied volatility should be considered part of a forecast but not the entire forecast, instead one should look at the entire information set available to market participants.

Day and Lewis (1992), which also looks at call options on the S&P 100 index, look into information content of implied volatility in regards to a GARCH and Exponential GARCH model. Their in sample results suggest that implied volatility contains information on the conditional volatilities from their GARCH models, and that their GARCH models contain information on the future implied volatility. When they tested the data on an out of sample comparison, they found similar results that there is no strong information content to implied volatility. They concluded that it is a biased forecast.

Lamoureux and Lastrapes (1993) look at options on ten individual stocks as opposed to an index. They differ from Day and Lewis (1992) by using daily data and through paying closer attention to measurement issues by using intraday data. Just as Day and Lewis (1992) discover that implied volatility contains information on the GARCH models which used historical realized volatility, Lamoreux and Lastrapes acknowledge that "implying variances under Black-Scholes distorts the actual variance under the null hypothesis" (p. 296). Their paper actually tests to quantify this effect. Ultimately, they come to a similar conclusion to Day and Lewis (1992).

Christensen and Prabhala (1998) on the contrary find that in S&P 100 index options, implied volatility does have forecasting ability of future realized volatility. They attribute the difference in findings to a longer data set and most importantly no overlapping data. They look at individual one month periods. The paper also finds that implied volatility in the period after the 1987 stock crash contains more information on realized volatility than prior to the crash. Earlier papers discussed above did not branch the crisis.

Jian and Tian (2005) derive implied volatility from a model-free approach derived by Britten-Jones and Neuberger (2000), as opposed to from the Black Scholes model, to test the forecasting ability of implied volatility on future realized volatility. Like the Christensen and Prabhala (1998) paper they do not use overlapping periods. The advantages to their approach is that it collects information from all strikes as opposed to just ATM, and that it is a purer test of the option market's efficiency. Presumably, in an efficient market, implied volatility should contain more information than historical volatility due to its forward looking nature and the no arbitrage conditions of the pricing model. The paper concludes that the model-free implied volatility contains more information present in Black Scholes implied volatility and historical realized volatility, and is therefore a better and more efficient forecaster of future volatility.

While Jorion (1995) did not add tremendously to the literature of implied volatility's forecasting ability, the paper did apply the previous research on equity options to currency options. The paper finds strong evidence that implied volatility outperforms other models in forecasting. However, it also concludes that in the FX space, the implied volatility is a biased forecaster such that implied volatility forecasts a more variable future volatility than actually seen.

The specific literature on implied correlations in currency options is substantially more limited. There are two main papers on the topic, Campa and Chang (1998) and Walter and Lopez (2000).

Campa and Chang (1998) use daily OTC option data on the USD/DEM/JPY currency trio for the period of January 1989 to May 1995. They judge the forecasting abilities of implied correlation against JP Morgan RiskMetrics, Historical Correlation, and a Bivariate GARCH model. In addition to a "horse race" regression they compute the bias of the forecast and look at statistical loss measures such as RMSE. They find that not only does implied correlation make the best forecast as a standalone measure, but that it is the only forecast to consistently add information to the others.

Walter and Lopez (2000) look at implied correlations for the USD/DEM/JPY and the USD/DEM/CHF currency trio. They note that the latter trio has significantly different characteristics and conclude that its implied correlation is a much weaker forecaster. Thus it raises the question of why implied correlation is a good forecaster of future realized correlation for the USD/DEM/JPY trio but not for USD/DEM/CHF.

It is important to note that Chong (2004) looks at the benefit of using implied correlations to forecast future realized correlation through a trading model. While it does not add to the literature on the forecasting ability, the paper does show real world significance in using a forecasting model based on implied correlations or a GARCH model.

Chen and Leung (2005) stipulate that they are in concurrence with Walter and Lopez (2000) and Campa and Chang (1998), in the fact that implied correlation has some forecasting ability. Their paper although retesting this, looks to see if it outperforms two Neural Network models. They find that implied correlation contains more information and is a better forecaster for future realized correlation than their nn models. That being said, they do find evidence that some combinations of the two models and implied correlation could create synergies that together could outperform implied correlation alone.

A November 1997 Bank of England Quarterly Bulletin titled "Implied exchange rate correlations and market perceptions of European Monetary Union" by Creon Butler and Neil Cooper calculates a forward implied correlation curve. Their methodology is simple, they derive the forward implied correlation from the forward implied volatility, in the same manner implied correlation can be backed out of implied volatility for any currency option trio. Implied Volatility is forward looking, as is the implied correlation that is derived from it. Thus, a one month option contract contains information of the implied correlation for that month. The implied correlation would be an average level for the period. Creating a fluid forward curve, through bootstrapping available option tenors would show future shorter term implied correlation, and provide one with much more information on the path of implied correlations. While the paper looks at the forward implied correlation to gain insight into the markets view on the probability of European Monetary Union, they are essentially creating another way to predict future realized correlation, which is not examined in any of the literature. To date, no research has been done on the forecasting ability of forward implied correlation, and this is a potential area of interest for future research

There is room in the literature to study why certain currency pairs' implied correlation is not good at forecasting. The Walter and Lopez (2000) paper simply establishes that there is some distribution or differences to the forecasting ability of implied correlation. My paper will look to fill this void.

III. Methodology

Computing Correlation

I replicate some of the methods in the Walter and Lopez (2000) paper. While they go through great statistical and econometric means to prove that implied correlations are the best forecasters of realized correlation. Although I accept their findings, whether or not implied correlation is the best forecaster or contains more information, its current superiority is not of tremendous importance. It is enough to establish that the forecasting ability of implied correlations varies, thus proving that the option market is more efficient for certain currency pairs. Walter and Lopez (2000) derived the forecasting coefficient by regressing implied correlations on realized correlations.

Implied correlation is a factor in many exotic options, where the payout or the strike is dependent on a currency different than the underlier. However, in currency options, implied correlation is present in vanilla options given any three currencies. Given currencies A, B, and C we can make currency pairs A/C, B/C, and A/B.

Equation1

$$\sigma^2_{A/B} = \sigma^2_{A/C} + \sigma^2_{B/C} - 2\rho(_{A/C,\ B/C})\sigma_{A/C}\,\sigma_{B/C}$$

Equation 2

$$\rho(A/C, B/C) = \rho(C/A, C/B)$$

Equation 3

$$\rho(_{A/C,\ B/C}) = \frac{\sigma^2_{A/C} + \sigma^2_{B/C} - \sigma^2_{A/B}}{2\,\sigma_{A/C}\,\sigma_{B/C}}$$

Equation 4

$$\rho(A/B, B/C) = -\rho(B/A, C/B)$$

Equation 5

$$\rho(_{A/B,\ B/C}) = \frac{-\sigma^2_{A/B} - \sigma^2_{B/C} + \sigma^2_{A/C}}{2\,\sigma_{A/B}\,\sigma_{B/C}}$$ [1]

For implied correlations, it is easiest to think of currency trios or triangles. The diagram on the next page[2] shows how using the law of cosine, one can manipulate the implied correlation formula given above, to create a triangle with the interior angles representing the implied correlation and the length of the sides being the implied volatility.

[1] Walter and Lopez (2000)
[2] Walter and Lopez (2000) The Shape of Things in A Currency Trio

Exhibit 1:
Volatility and correlation triangle for the USD/DEM/JPY trio (8-SEP-1998)

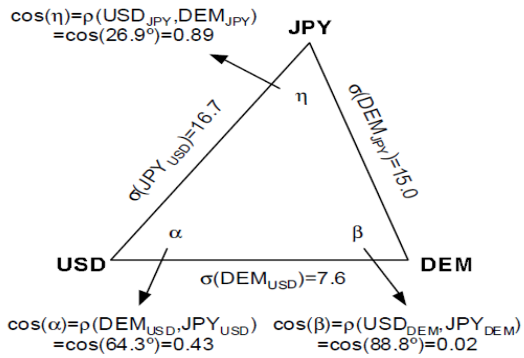
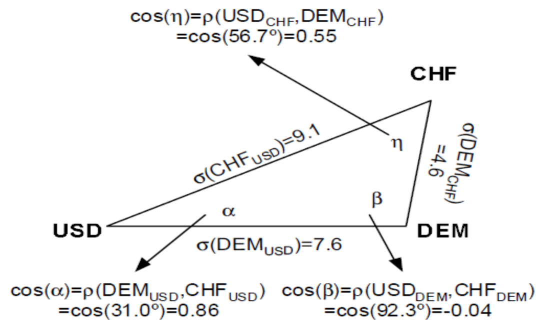


Exhibit 2:
Volatility and correlation triangle for the USD/DEM/CHF trio (8-SEP-1998)



If the graphical representation is not helpful, one can note the three different currency pairs present in the formula, to realize that in order to back out an implied correlation you need groups of three pairs. Out of my fifty six currency pairs, I created thirty two of these trios. I then broke up the fifteen year period into three five year periods, thus creating essentially ninety six trio periods.

To calculate realized correlations, rcorr, is derived from the difference of lognormal of the exchange rates. I then computed a rolling correlation, using the command MVCORR with a twenty two day window. Twenty two days is the average length in trading days of a one month option contract. I replicated the data with a rolling window of twenty and twenty four days respectively, and there was no statistical difference. This of course makes sense, as the adjunct of another two days would not be able to greatly change the correlation over the entire period.

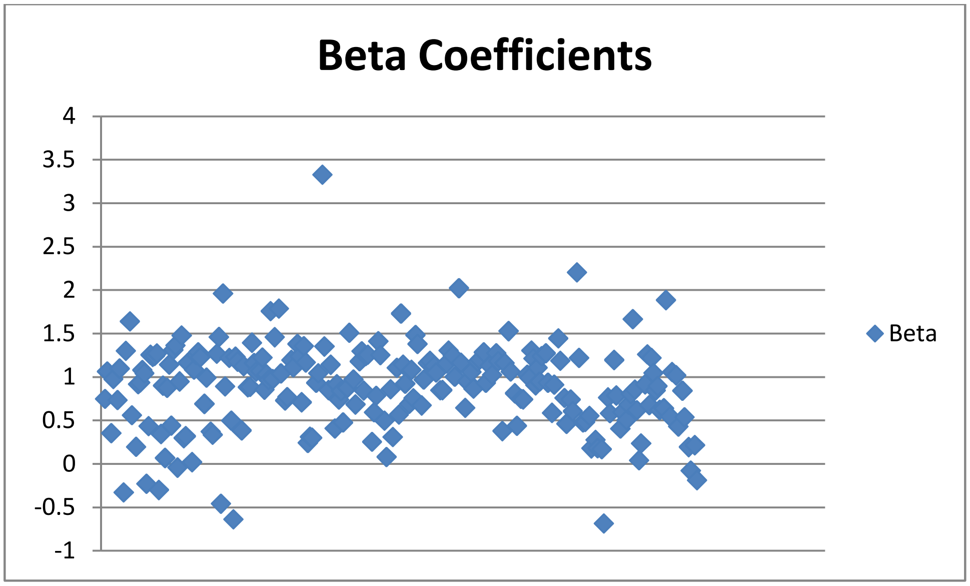
Dependant Variables

I regressed the implied correlations on the realized correlations. It is important to note that the realized correlations were counted on a forward rolling basis to match the period over the life of the option. Following the Walter and Lopez (2000) paper, I used a Newey West regression that adjusts the standard errors from the autocorrelation that exists due to using overlapping data. Not surprisingly, the necessary window to adjust for the autocorrelation needed in the Newey West regression was also approximately twenty two days. However, it is important to note that in replicating my thesis, using Newey West would not be necessary, as it solely adjusts the significance of the beta coefficients not their levels. Although the overwhelming majority of the beta coefficients when adjusted were significant, I did not drop a currency trio if its beta coefficient was not significant, as it would bias my sample.

Equation 6

$$\rho_{realized} = \alpha + \beta\, \rho_{implied} + \epsilon$$

If implied correlation is a good forecaster of future realized correlation, the beta coefficient in the above equation should equal one. Accordingly, if my thesis is looking to prove that there are factors that affect this forecasting ability, it is essential, that the forecasting ability varies over the different currency trios.



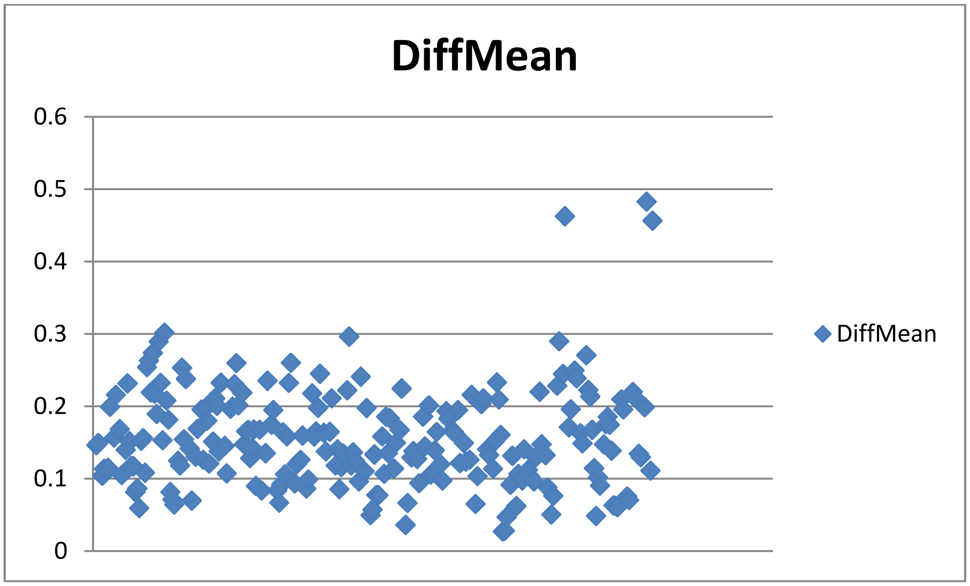
The above graph shows that the beta coefficients are adequately distributed across a range -.686 to 3.26. While a negative value does not make sense given the regression, with an average of .8866 and a standard deviation of .4965[3], the negative values can be explained by a statistical blip.

These beta coefficients now become my dependant variables in a cross sectional regression looking to explain their variation. All of my independent variables for this cross sectional had to be derived and generated from the time series data I collected that was described earlier in the data collection section.

Additionally, I look at another proxy for forecasting power to serve as the dependant variable in the cross sectional regressions. The variable, titled diffmean, is the absolute value of the time series difference between implied correlation and realized correlation averaged over each five year period for the respective correlations. It is the average prediction error over the

[3] When only looking at the most recent 10 years, for which the data is complete the average is .9191 with a standard deviation of .4680.

five year period. While it does not contain as much information on forecasting as the betas, it does a better job of capturing the risk of one's prediction (implied correlation) straying from reality (realized correlation).



The above graph shows that the prediction error for the 288 correlations calculated varies from .027 to .485. As with the betas, the prediction errors are evenly distributed across the different currency pairs. While it is not clear if this paper will be able to explain the variation, there clearly exists a variation in the size of the prediction error across currency pairs.

Beta shows the accuracy of the forecast, while diffmean shows the prediction error. Since impcorr is forward looking, to a period equal to the realized correlation, a beta coefficient of one implies that implied correlation, which contains the markets predictions, moves in tandem with actual future changes in realized correlation. It shows accuracy over time. Diffmean, on the other hand, shows the average level the implied correlation differed from realized correlation on each and every option. It gives a greater sense of the magnitude and frequency of a prediction error.

While, the variable diffmean, the absolute value of the difference between the implied correlation and realized correlation, is a good indicator of prediction error risk there are other possible variables that due to data restrictions I could not use. One such proxy for strength of forecasting would be the R squared of the regression that produced the beta coefficients. However, without using Newey West to adjust for the autocorrelation from the overlapping data, the R squareds were all sufficiently high and did not vary. Unfortunately, the Newey West regression did not give an R squared output.

Independent Variables

The variables generated for the cross sectional regressions fit into three different categories. Variables describing the correlations both implied and realized and their interaction with one another, those describing the implied volatilities of the options from which implied correlations are derived, and the liquidity of the options. In terms of a currency triangle, the three categories look at characteristics of the angles, the perimeter of the triangle and the length of individual sides, and the liquidity of the triangle as a whole as well as for each individual side.

The variable impcorrmean is defined as the average level of implied correlation over the five year period for a given correlation, and was calculated from the implied correlations used in the time series regression that produced the beta coefficients. I also computed the average level of realized correlation over the five year period for a given correlation and titled the variable rcorrmean. The hypothesis is that the levels of correlation would affect the attention market makers and investors would pay to correlation when making prices on the vanilla options.

The standard deviation of implied correlation and realized correlation over each five year period for a respective correlation were titled impcorrstd and rcorrstd, and were calculated in the same manner as the average levels for these variables. The initial hypothesis for these variables' significance, would be that a forecaster or its target that moves a lot would be less efficient at forecasting.

The absolute value of the difference between the average levels of implied correlation and realized correlation is the variable diffafter, and it was calculated by the absolute value of the difference between the average level of implied correlation and realized correlation for each five year period. As opposed to the variable diffmean discussed in the previous section, this is a proxy for the size of the risk premium rather than the prediction error, as it captures the difference between the average, steady state levels of implied and realized correlation, as opposed to the average miss between implied and realized correlation. It is important to note that I tested the significance of the absolute difference as well as the general difference. Whether or not the implied correlation over or undershot realized correlation was less significant.

The standard deviation of the prediction error for each five year period, would be the standard deviation of the data that generated diffmean. It shows the volatility of the prediction error. In this sense, it shows the risk that one's prediction error risk will spike. It is labeled the variable diffstd.

The percent of observations of implied correlation available for each approximately five year period, or 1309 data points, is noted by the variable percentobsimp. It is a proxy for liquidity. I also calculated this variable for realized correlation. The former measures the liquidity in the options market while realized reflects spot. Spot has significantly more liquidity, and therefore less variation in this variable, and I do not expect it to be as significant as for implied correlation.

I generated various statistics based off the bid-ask spread as a percentage of implied volatility for the three currencies that made up each implied correlation. It is important here to understand that implied correlation between A/C and B/C is derived from the implied volatilities of A/C, B/C, and A/B. Thus for a given implied correlation, the corresponding data point for the bid-ask spread as a percentage of implied volatility, needs to be an average of the three currency pairs. So, to calculate the variable bapercentmean, or the average level bid-ask spread as a percentage of implied volatility, I first had to calculate the average spread between each of the three currency pairs for every day of data over the period. The average level of that number for each five year period would be the bapercentmean. The bapercentstd would be the standard deviation of the average for the three pairs for the respective period. Both are proxies of liquidity for the currency trio as a whole, as they are derived from average levels across the three currency pairs. The variable bapercentmean would be general liquidity risk, while bapercentstd is the risk of a liquidity shock. It is important to reiterate, that these variables are in terms of percentage of implied volatility, as the level of implied volatility is accounted for by the variables directly derived from implied volatility.

The same issue described above that a given correlation is derived from the three options. Thus using the same methods, I generated the variable impvolmean, or the mean level of the average implied volatility for the three currencies pairs that make up the currency triangle. I used the same one month ATM straddle volatility used in the time series regression that produced the beta coefficients. Likewise, this gives a view of the volatility for the whole currency triangle. It also means that for a given three implied correlations of a currency triangle, each of the correlations will have the same impvolmean value. Since given three implied volatilities the corresponding correlations are certain, but given three correlations the level of the three implied volatilities is not known, this variable provides unique information on the shape, and therefore characteristics of the currency triangle. The standard deviation of the average implied volatilities is measured by the variable impvolstd and provides some insight into how the currency triangle changes shape.

The variables -bapercentmean, bapercentstd, impvolmean, and impvolstd are all derived from the average levels of the three currency pairs that make up each currency trio. Yet, there is no economic reasoning to assume that market participants would look at the average level to represent the trio's characteristics. They could for instance price to worst, in the sense that a currency triangle with two liquid currency pairs and one illiquid one, would be priced to the illiquid one. This would even be more rational since the "weakest link" is a limiting factor. Thus, I recreated the four variables listed above, generating the means and standard deviations from both the minimum value in trio and another set of variables from the maximum value. These variables better show the effects of individual pairings on the forecasting performance of correlations in a trio. They would provide insight into the effects of uniquely shaped currency triangles, which are such shaped due to one of the three pairs.

IV. Data

The option data used to derive the implied correlation is comprised of the last traded prices of one month atm straddles from 56 different currency pairs, for a fifteen year period from 1995-2010 pulled off bloomberg. The 56 pairs reflected all the possible pairs within the G10 and several common pairings with emerging market currencies. I chose atm straddles because the effect of the volatility skew would be minimized. Additionally, they are consistent with the previous literature. Jian and Tian (2005) computed the implied volatility in a model free approach from a range from deltas and tenors. While their results are more significant as they do not rely on Black Scholes, the rest of the literature and market practice[4] uses Black Scholes. Additionally, the Bid price and the Ask price for the options as well as the last traded spot data for the same period was also provided by Bloomberg. My data could be improved upon by getting the direct data from various sell side firms or brokerages. Furthermore, comparing the implied volatility from an exotic option to that derived from vanilla options would be interesting, as direct attention is given to implied correlation in the exotic option pricing.

V. Results

Table 1 to Table 10 show various regressions with beta as the dependant variable, while Table 11-Table22 contain diffmean as the dependant variable. As discussed, both variables provide unique insights into the variation of how implied correlation forecasts or predicts realized correlation across different currency pairs.

I ran all the regressions discussed below for the entire dataset of all fifteen years, as well as for only the last ten years. The reasoning behind this was completeness of data. I had relatively uniform data for all my correlations for the last ten years, but the dataset was very incomplete for the first five year period. However, as you will note in tables 6-10 and 17-22, my

[4] While black schools is not used to price options, market makers quote prices using Black Scholes imp vol.

results are generally consistent over the course of the entire data set. Any slight differences are due to the poor dataset for the first five year period.

Table 1 shows the dependant variable beta being regressed on all the independent variables. As the variables are generated from similar data, and within the three groups described above, explain characteristics of the same three inputs in slightly different ways, there is correlation between all the variables and not much is significant. However, impcorrstd, rcorrstd, and diffmean are significant and robust. In order to find my final most significant and robust regression model, I determine the most efficient model for each group.

Table 2 looks for the most significant and robust variables describing characteristics of the correlation and its forecasting ability. Table 2 shows that the average levels of realized and implied correlations, impcorrmean and rcorrmean are accounted for by variable diffafter and are therefore correlated. While it is obvious that impcorrmean and rcorrmean are also correlated with one another, impcorrmean along with diffmean and diffafter contain more information than the levels of correlation alone and are therefore the better and more robust variables.

Table 3 looks to find the most significant and robust model for the liquidity measures after building upon the findings from Table 2. Essentially, it is building the model from the bottom up. As discussed, liquidity can be measured for the average level for currency triangle as a whole, or through a price to worst (best) mentality, where the least (most) liquid pair dictates the liquidity for the whole triangle. Table 3 determines that when just defining liquidity as the average level for the whole triangle both the average level and the standard deviation for the five year period is significant, but that the average level of liquidity, represented by the variable bapercentmean contains information provided by the standard deviation and more and is thus robust. This makes intuitive sense, for if the liquidity premium changes often, one faces a greater risk of lack of liquidity, and the level of the bid ask spread would increase to show that.

When only considering the minimum bid ask spread variables, or the most liquid pair in the trio, neither variable is significant. When examining the least liquid pairing in the trio, defined by bapercentmax variables, the results are similar to the average levels discussed in the previous paragraph. Finally, the percent of observations present, which is another variable showing the effects of the least liquid pairing on the trio is also significant.

Table 4 determines which of the significant variables found in table 3 is the most robust and creates the best model. The variable bapercentmaxmean, or the average level of the least liquid pair in a trio proves to be me the most robust variable between the liquidity variable for the average level of liquidity for the triangle on a whole (bapercentmean) and the alternate price to worst variable percentofobsimp. It is logical that the average level for the triangle on a whole would be less robust than the maximum level but still significant, because having one currency pair that is definitively less liquid than the others would raise the average. Since liquidity for those pairings which are liquid is fairly constant, an illiquid pair within a trio would change the average enough from the other correlations to have significance. However, the magnitude of the change would not be a great as if we were just measuring the least liquid pair, and thus it is less robust.

Table 5 examines, once again after building on top of the information provided from previous tables, the effects of characteristics of the implied volatility on the variation in forecasting ability. It shows that none of the variables derived from the level of implied volatility are significant in addition to the existing model in explaining the forecasting ability of implied correlation. Since implied correlation is a function of implied volatility, the two should and are correlated. Yet, when impcorrstd is dropped from the regression, eliminating the correlation problem, it is clear that impcorrstd contains more information and is a better explanatory variable.

Thus my strongest model for explaining the variation in the beta coefficients is impcorrstd rcorrstd impcorrmean diffmean diffafter bapercentmaxmean.

The coefficients on diffmean, diffafter, and bapercentmaxmean are relatively easily explained. As stated, diffmean is a proxy for prediction error, and an increase in diffmean would mean that magnitude of large differences between implied and realized correlation or the frequency of average misses is increasing. An increase in either the size or frequency of bad forecasts would decrease the forecasting coefficient.

Option prices are forward looking and reflect given a defined set of information the market's prediction of realized values over the tenor.   It is this forward looking behavior, that is credited for options' superior forecasting ability. Yet, as with any asset, on top of the expected or intrinsic value lies a premium. The larger the risk premium, the higher the option price. The market price reflects the intrinsic value plus any premiums. Since implied correlations are derived from the market price, but their supposed forecasting abilities come from their forward looking nature's ability to assign an intrinsic value, any divergence from the price reflecting the intrinsic value would decreasing the forecasting ability of implied correlations. Thus, the diffafter as a proxy for risk premium should and does have a negative coefficient. Additionally, as a proxy for the liquidity premium, bapercentmaxmean also has a negative coefficient. In summary, the more of an options price that does not reflect the markets prediction of future value, the worse of a forecaster implied correlation will be.

The coefficient on impcorrmean is less intuitive. Since correlation has an upward bound of one, the higher the correlation is the less possible volatility that could be present, as the underlier can only move in one direction as opposed to two. Summary statistics prove this and show a lower impcorrstd for the higher impcorrmeans. Essentially, this explanation shows that impcorrmean contains a lot of the same information as impcorrstd, but since the strength of the relationship between the two variables greatly varies across different levels of impcorrmean, impcorrmean does not shed light on all of the explanatory information that impcorrstd clearly contains. Since it is related to both impcorrstd as well as the difference variables, my hypothesis that it is a control for the other variables.

You will notice a negative coefficient for the standard deviation of implied correlation, but a positive coefficient for the standard deviation of realized correlation. The coefficient for the standard deviation of implied correlation makes more intuitive sense. As implied correlations move around more, their forecasting ability decreases. Higher volatility of a factor simply makes forecasting more difficult. Yet, a positive coefficient could be justified as well. A higher impcorrstd implies a more volatile implied correlation. If the implied correlation moves more often in response to news, it would be considered to have more information and would be a better forecaster and thus have a positive coefficient. Yet, this would only be true if the movement in the implied correlation was from market participants changing their market price in an attempt to better forecast correlation. If in fact, implied correlation were to change due to exogenous shocks in implied volatility with no thought given to or having no effect on implied correlation, this would not hold. Additionally, if just one of the pairings in the trio received an exogenous shock to their volatility, it would change the shape of the "triangle" and therefore change all three angles or implied correlations. Thus, a positive sign would only make sense if the increase in impcorrstd was related to the market forecasting correlations, not necessarily as a byproduct of fluctuations in the overall option price.

Yet, how do we explain the positive coefficient for the standard deviation of realized correlation? How does a more volatile realized correlation increase the forecasting ability of implied correlation?

Implied correlation is derived from options. Options are a forward looking instrument, and for the most part are priced by investment professionals. If the level of realized correlation is constant, market makers tend to forget about correlation as a factor. While it is anecdotal, I spoke with four traders about the issue of correlation, all but one of whom trade fx options, and the fourth trades index volatility, which relies heavily on correlation, and they all had the same viewpoint. Correlation based trading and the focus on correlation only occurs when correlation moves. People tend to forget about correlation when it is constant, and particularly low. Thus, market makers of options often disregard correlation and its potential movements in making their prices.

It is believed that the options market is a good forecaster of future realized factors because it is an intelligent forward looking instrument. Its price reflects the forward looking opinion of market participants. Thus, it follows that when market participants focus on correlation when making option prices in addition to focusing on volatility, the options will reflect implied correlations that are better forecasters of future realized correlation.

Market makers in FX options are wearing blinders. Desks are set up so that each trader focuses on one currency's volatility space. For example, there is a Euro trader and a Yen trader, so for most currency trios, there are two traders responsible for making prices in the three pairs. Vanilla option traders are not looking at their product from a view where implied correlation is relevant, and their ability or the reality of them colluding with the other members of the desk is limited.

Although the above solution is only a possibility, it is essential to note that the signs remain consistent and significant and cannot be explained away through a correlation with the difference variables. So, whatever the reasoning may be, the data strongly points to the two having different signs.

Another possible explanation for the difference in signs is more mechanical. When implied correlation is higher than realized correlation, and implied correlation is used to forecast realized correlation, the beta will be less than one. Accordingly the reverse would also be true.

The above results are similar when diffmean is the dependant variable, save certain differences. We gain insight in examining how the significance of the independent variables differ with the change in the dependant variable.

Again, the signs for impcorrstd and rcorrstd do not make intuitive sense initially. Assuming that beta and diffmean both provide some insight into the quality of forecaster that implied correlation is of future realized correlation, the signs should not be the same between the two regressions. While a negative sign with beta as a dependant variable indicated that the forecasting ability decreased as impcorrstd increased, a negative sign with diffmean as the dependant variable indicates that the prediction error decreases as impcorrstd increases, and thus the forecasting ability increases. The same is true in reverse for rcorrstd. If the explanations given above, and the regressions with beta as the dependant variable are to be considered valid, there must be another explanation.

Implied correlations and future realized correlations are obviously linked as the former is a forecaster of the latter. Additionally, we know that there is a relationship between the standard deviation of correlation and the level, due to their being an upper and lower bound. From the distribution of betas, we also know that implied correlations tend to trend to overestimating realized correlation, and thus we can conclude implied correlations tend to be higher, or closer to one than realized correlations. Therefore, due to the upward bound, a higher impcorrstd would lower the level of implied correlation. Lowering the level of an over estimator would decrease the prediction error. Likewise raising the standard deviation of realized correlation would lower the level of realized correlation, thus increasing the prediction error.

Table 13 shows that again, bapercentmean is significant, but only when bapcercentstd is included in the regression, and neither variable is significant independently. Table 14 shows similar results for the bapercentmaxmean and bapercentmaxstd. While the significance of the two variables for the average level of liquidity is not different with this new dependant variable, their relationship with the standard deviation is. More importantly, the sign for bapercentmean and bapercentmaxmean indicate a different effect of liquidity on the prediction error than for the regressions with the beta variable as the dependant variable. However, the sign for the standard deviations is correct and consistent. I have no explanation for why an increase in the bid ask spread would decrease the prediction error, as it goes against all economic rationale. Yet, it is important to note that the variable is not highly significant, and its economic significance seen by the coefficient, is dramatically less than it was for the cross-sectional regression with beta as the dependant variable.

It is also important to try and explain why bapercentmaxmean and bapercentmean are only significant when their standard deviations are included in the regression. The results are saying, that in explaining the variations in the prediction error, the significance of the liquidity risk premium, whether it is for the least liquid pairing or for the trio as a whole, is more dependent on the risk that the risk premium changes (bapercentstd and bapercentmaxstd). In analyzing the results for the first regression with beta as the dependant variable, it was concluded that the significance of the liquidity premium, is due to less of the option's price from which implied correlation is derived reflecting the market's forward looking predictions. From the explanation given above, on due to how diffmean is derived why a negative coefficient makes sense for impcorrstd, we can also conclude that structurally the negative coefficient on bapercentmaxmean and bapercentmean is correct.

VI. Conclusion

The paper establishes that not all implied correlations are created equal. Some are better forecasters of future realized correlation than others, and in fact their forecasting ability varies greatly. Despite using two different proxies for capturing this forecasting ability, their variability was consistent. Regardless of my success in explaining this variation, simply finding the variation is of tremendous importance. The variation in forecasting ability, says that the options markets for different currency pairs contains different amounts of explanatory information on future events. Our understanding or attention paid to correlations varies across currencies.

Additionally, it would be interesting to do a similar methodology on other markets. For instance, does this variation exist solely because implied correlation is a secondary function in the options price, or would the forecasting abilities of implied volatility for future realized volatility vary across currency pairs as well? Furthermore, when correlation is a direct and deliberate input, such as in exotic options prices, does the forecasting ability still vary?

The paper then attempts to explain that variation. On this note, it neither fails nor passes. For my first dependant variable, beta, some of the variation is explained, approximately forty percent, but the economic rationale behind the coefficients is not abundantly clear, and there clearly is omitted variable bias. While I stand by my possible explanations for the different signs on the coefficients between implied and realized correlation, it is still just a possible explanation.

When diffmean which was a proxy for prediction error was used as the explanatory variable, the regressions had a R squared of over 80%. However, as discussed in the results section, there seems to be a structural explanation for the interesting results due to how the dependant variable is defined rather than an economic rational.

Ultimately, the less than stellar findings for an explanation for the variation in forecasting, is due to my incomplete data, as well as correlation between my variables. I looked at ATM straddles for one tenor, if the data was available it would be interesting to look at my thesis across all deltas and tenors. Additionally, I would be able to get a more complete dataset if I were to get option prices from various sell side market makers.

That being said, the research suggests a potential mispricing of implied correlations in option prices. It was not fully considered in this paper that correlation may be a more random and therefore harder to forecast variable than volatility, and thus the variation in forecasting ability is simply from noise. In that case, the logic would follow that correlation is random and thus implied correlation's ability to forecast would also be random. While this explanation is a possibility, my paper would tend to disagree and makes the argument that correlation and its propensity to move, is not often considered when making a vanilla options price.

This would create a possible trading strategy where one gets access to properly priced correlation through the exotics market, and then goes long or short the correlation in the vanilla market depending on the mispricing. Additionally, if one has faith in their correlation forecast over the market's often biased forecast, there is a trade opportunity within just the implied volatility in vanilla options. So, if correlation can be forecasted, there is clearly an economic benefit to better understanding it.

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VIII. Appendix

Table 1

Variable	beta
impcorrstd	-1.678**
	(0.731)
rcorrstd	3.495***
	(0.588)
impcorrmean	0.558*
	(0.292)
rcorrmean	-0.391
	(0.299)
diffmean	-2.121**
	(0.929)
diffafter	-0.511
	(0.489)
diffstd	-0.400
	(0.990)
percentofobsimp	0.163
	(0.158)
bapercentmean	3.103
	(3.731)
bapercentstd	-8.205
	(11.83)
bapercentminmean	3.179
	(2.648)
bapercentminstd	-4.412
	(8.617)
bapercentmaxmean	-3.402*
	(1.773)
bapercentmaxstd	2.466
	(3.946)
impvolmean	0.128
	(0.178)
impvolstd	-0.0142
	(0.208)
impvolminmean	-0.0326
	(0.0709)
impvolminstd	-0.0242
	(0.0948)
impvolmaxmean	-0.0770
	(0.113)
impvolmaxstd	0.00777
	(0.132)
Constant	0.749***
	(0.242)
Observations	192
R Squared	0.447
Adjusted R Squared	.382

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 2

Variable	beta	beta	beta	beta
impcorrstd	-2.057***	-2.766***	-2.691***	-2.068***
	(0.568)	(0.446)	(0.447)	(0.441)
rcorrstd	3.922***	2.498***	2.534***	3.962***
	(0.538)	(0.492)	(0.496)	(0.527)
impcorrmean	0.471	0.749**	0.178***	0.155***
	(0.290)	(0.298)	(0.0601)	(0.0551)
rcorrmean	-0.330	-0.601*		
	(0.296)	(0.307)		
diffmean	-2.195**			-2.205***
	(0.937)			(0.676)
diffafter	-1.351***			-1.480***
	(0.455)			(0.439)
diffstd	-0.104			
	(0.924)			
Constant	0.679***	0.660***	0.634***	0.664***
	(0.0963)	(0.103)	(0.103)	(0.0947)
Observations	192	192	192	192
R Squared	0.348	0.217	0.201	0.344
Adjusted R Squared	.323	.201	.189	.326

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 3

Variable	beta	beta	beta	beta	beta	beta	beta	beta
impcorrstd	-1.983***	-2.247***	-1.836***	-2.399***	-2.327***	-2.464***	-2.439***	-2.454***
	(0.480)	(0.457)	(0.448)	(0.436)	(0.483)	(0.454)	(0.466)	(0.427)
rcorrstd	3.691***	3.864***	3.744***	3.974***	3.846***	3.773***	3.624***	3.867***
	(0.524)	(0.519)	(0.530)	(0.510)	(0.526)	(0.519)	(0.530)	(0.501)
impcorrmean	0.177***	0.169***	0.162***	0.167***	0.166***	0.177***	0.171***	0.175***
	(0.0525)	(0.0534)	(0.0546)	(0.0534)	(0.0545)	(0.0528)	(0.0541)	(0.0525)
diffmean	-2.265***	-2.097***	-2.038***	-2.177***	-2.023***	-2.031***	-1.743**	-2.154***
	(0.659)	(0.657)	(0.672)	(0.654)	(0.671)	(0.666)	(0.677)	(0.642)
diffafter	-0.797*	-1.075**	-1.546***	-0.987**	-1.094**	-0.773*	-1.030**	-0.772*
	(0.461)	(0.452)	(0.435)	(0.445)	(0.479)	(0.462)	(0.466)	(0.444)
percentofobsimp					0.325***	0.0520	0.280***	
					(0.111)	(0.122)	(0.101)	
bapercentmean	2.586	-2.542***		-2.858***				
	(3.495)	(0.819)		(0.766)				
bapercentstd	-11.33	-2.948	-5.917**					
	(9.619)	(2.704)	(2.588)					
bapercentminmean	2.630				3.098			
	(2.530)				(2.059)			
bapercentminstd	-1.215				-7.802			
	(7.753)				(6.169)			
bapercentmaxmean	-3.289*					-1.728***		-1.934***
	(1.695)					(0.536)		(0.418)
bapercentmaxstd	3.508					-0.727	-2.055**	
	(3.268)					(1.034)	(0.972)	
Constant	0.895***	0.941***	0.784***	0.909***	0.455***	0.922***	0.618***	0.945***
	(0.117)	(0.116)	(0.107)	(0.113)	(0.128)	(0.145)	(0.112)	(0.108)
Observations	192	192	192	192	192	192	192	192
R Squared	0.432	0.393	0.362	0.389	0.373	0.414	0.380	0.412
Adjusted R Squared	.397	.370	.341	.370	.346	.388	.357	.393

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 4

Variable	beta	beta	beta	beta
impcorrstd	-2.474***	-2.506***	-2.418***	-2.454***
	(0.451)	(0.469)	(0.427)	(0.427)
rcorrstd	3.767***	3.876***	3.781***	3.867***
	(0.505)	(0.521)	(0.503)	(0.501)
impcorrmean	0.179***	0.163***	0.178***	0.175***
	(0.0526)	(0.0545)	(0.0524)	(0.0525)
diffmean	-2.111***	-2.012***	-2.143***	-2.154***
	(0.647)	(0.671)	(0.640)	(0.642)
diffafter	-0.676	-1.019**	-0.722	-0.772*
	(0.461)	(0.471)	(0.444)	(0.444)
percentofobsimp	0.0455	0.256**		
	(0.116)	(0.102)		
bapercentmean	3.009		2.909	
	(2.078)		(2.057)	
bapercentmaxmean	-3.387***		-3.438***	-1.934***
	(1.152)		(1.142)	(0.418)
Constant	0.875***	0.536***	0.914***	0.945***
	(0.148)	(0.106)	(0.110)	(0.108)
Observations	192	192	192	192
R Squared	0.419	0.365	0.418	0.412
Adjusted R Squared	.393	.345	.396	.393

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 5

Variable	beta	beta	beta	beta	beta
impcorrstd	-2.162***	-2.205***	-2.209***	-2.210***	
	(0.509)	(0.500)	(0.497)	(0.492)	
rcorrstd	3.907***	3.932***	3.889***	3.973***	3.581***
	(0.542)	(0.525)	(0.528)	(0.516)	(0.535)
impcorrmean	0.182***	0.181***	0.179***	0.183***	0.193***
	(0.0541)	(0.0532)	(0.0534)	(0.0531)	(0.0557)
diffmean	-2.413***	-2.324***	-2.304***	-2.355***	-3.643***
	(0.675)	(0.665)	(0.662)	(0.666)	(0.632)
diffafter	-0.720	-0.809*	-0.803*	-0.804*	-0.741
	(0.457)	(0.447)	(0.447)	(0.446)	(0.468)
bapercentmaxmean	-2.080***	-2.102***	-2.124***	-2.089***	-2.111***
	(0.459)	(0.449)	(0.454)	(0.446)	(0.468)
impvolmean	0.171	-0.000522			
	(0.155)	(0.0208)			
impvolstd	-0.0505	-0.0144			
	(0.183)	(0.0268)			
impvolminmean	-0.0585		-0.000594		
	(0.0640)		(0.0192)		
impvolminstd	0.00808		-0.0215		
	(0.0880)		(0.0291)		
impvolmaxmean	-0.111			-0.00356	0.00869
	(0.0958)			(0.0179)	(0.0186)
impvolmaxstd	0.0353			-0.00779	-0.0429**
	(0.113)			(0.0221)	(0.0217)
Constant	1.017***	0.997***	1.014***	1.014***	1.010***
	(0.205)	(0.173)	(0.153)	(0.172)	(0.181)
Observations	192	192	192	192	192
R Squared	0.422	0.415	0.416	0.416	0.352
Adjusted R Squared	.383	.390	.390	.391	.327

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 6

Variable	beta
impcorrstd	-2.133***
	(0.722)
rcorrstd	3.947***
	(0.588)
impcorrmean	0.362
	(0.303)
rcorrmean	-0.169
	(0.311)
diffmean	-2.843***
	(0.930)
diffafter	-0.511
	(0.505)
diffstd	0.285
	(0.999)
percentofobsimp	0.206
	(0.152)
bapercentmean	3.122
	(3.909)
bapercentstd	-10.56
	(12.34)
bapercentminmean	2.558
	(2.776)
bapercentminstd	-3.954
	(8.537)
bapercentmaxmean	-3.119*
	(1.844)
bapercentmaxstd	3.226
	(4.059)
impvolmean	0.144
	(0.184)
impvolstd	-0.0534
	(0.215)
impvolminmean	-0.0730
	(0.0691)
impvolminstd	0.00843
	(0.0922)
impvolmaxmean	-0.0941
	(0.118)
impvolmaxstd	0.0519
	(0.135)
Constant	0.926***
	(0.239)
Observations	204
R Squared	0.411
Adjusted R Squared	0.347

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7

Variable	beta	beta	beta	beta
impcorrstd	-2.117***	-2.671***	-2.626***	-1.953***
	(0.579)	(0.462)	(0.462)	(0.455)
rcorrstd	4.148***	2.517***	2.547***	4.121***
	(0.555)	(0.506)	(0.506)	(0.545)
impcorrmean	0.308	0.585*	0.186***	0.163***
	(0.300)	(0.307)	(0.0613)	(0.0566)
rcorrmean	-0.153	-0.419		
	(0.307)	(0.317)		
diffmean	-2.857***			-2.542***
	(0.938)			(0.684)
diffafter	-1.342***			-1.396***
	(0.469)			(0.450)
Constant	0.663***	0.635***	0.616***	0.652***
	(0.0987)	(0.106)	(0.106)	(0.0971)
Observations	204	204	204	204
R Squared	0.321	0.187	0.180	0.319
Adjusted R Squared	0.297	0.17	0.167	0.302

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8

Variable	beta	beta	beta	beta	beta	beta	beta	beta
impcorrstd	-1.803***	-2.128***	-1.783***	-2.232***	-2.239***	-2.432***	-2.386***	-2.288***
	(0.502)	(0.474)	(0.464)	(0.454)	(0.499)	(0.472)	(0.478)	(0.448)
rcorrstd	3.918***	4.063***	3.985***	4.129***	3.982***	3.946***	3.857***	4.053***
	(0.544)	(0.541)	(0.548)	(0.533)	(0.542)	(0.539)	(0.545)	(0.527)
impcorrmean	0.182***	0.176***	0.169***	0.174***	0.173***	0.184***	0.179***	0.181***
	(0.0548)	(0.0557)	(0.0565)	(0.0556)	(0.0558)	(0.0551)	(0.0558)	(0.0549)
diffmean	-2.665***	-2.465***	-2.436***	-2.514***	-2.344***	-2.313***	-2.130***	-2.496***
	(0.676)	(0.673)	(0.684)	(0.670)	(0.680)	(0.680)	(0.686)	(0.661)
diffafter	-0.803*	-1.042**	-1.438***	-0.989**	-0.975**	-0.679	-0.893*	-0.797*
	(0.474)	(0.466)	(0.449)	(0.460)	(0.487)	(0.477)	(0.476)	(0.462)
percentofobsimp					0.326***	0.150	0.305***	
					(0.107)	(0.118)	(0.103)	
bapercentmean	2.752	-2.242***		-2.437***				
	(3.703)	(0.828)		(0.788)				
bapercentstd	-12.02	-2.106	-4.338					
	(9.811)	(2.715)	(2.628)					
bapercentminmean	3.103				2.725			
	(2.601)				(1.958)			
bapercentminstd	-2.423				-6.188			
	(7.582)				(5.965)			
bapercentmaxmean	-3.222*					-1.313**		-1.682***
	(1.783)					(0.521)		(0.435)
bapercentmaxstd	4.124					-0.650	-1.498	
	(3.305)					(1.005)	(0.960)	
Constant	0.831***	0.881***	0.737***	0.855***	0.448***	0.791***	0.568***	0.888***
	(0.122)	(0.120)	(0.110)	(0.116)	(0.127)	(0.142)	(0.113)	(0.112)
Observations	204	204	204	204	204	204	204	204
R Squared	0.389	0.353	0.329	0.351	0.351	0.373	0.353	0.368
Adjusted R Squared	0.354	0.33	0.308	0.351	0.324	0.347	0.329	0.348

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9

Variable	beta	beta	beta	beta
impcorrstd	-2.433***	-2.424***	-2.256***	-2.288***
	(0.469)	(0.479)	(0.448)	(0.448)
rcorrstd	3.933***	4.014***	3.981***	4.053***
	(0.529)	(0.537)	(0.528)	(0.527)
impcorrmean	0.185***	0.172***	0.184***	0.181***
	(0.0548)	(0.0558)	(0.0548)	(0.0549)
diffmean	-2.380***	-2.312***	-2.488***	-2.496***
	(0.665)	(0.678)	(0.660)	(0.661)
diffafter	-0.594	-0.906*	-0.742	-0.797*
	(0.478)	(0.478)	(0.463)	(0.462)
percentofobsimp	0.139	0.279***		
	(0.113)	(0.102)		
bapercentmean	3.143		2.939	
	(2.174)		(2.170)	
bapercentmaxmean	-3.039**		-3.214***	-1.682***
	(1.218)		(1.212)	(0.435)
Constant	0.747***	0.514***	0.857***	0.888***
	(0.145)	(0.108)	(0.114)	(0.112)
Observations	204	204	204	204
R Squared	0.378	0.344	0.373	0.368
Adjusted R Squared	0.353	0.325	0.351	0.348

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10

Variable	beta	beta	beta	beta	beta
impcorrstd	-2.287***	-2.274***	-2.326***	-2.192***	
	(0.518)	(0.509)	(0.507)	(0.504)	
rcorrstd	4.246***	4.302***	4.273***	4.262***	3.864***
	(0.550)	(0.536)	(0.532)	(0.535)	(0.551)
impcorrmean	0.203***	0.197***	0.203***	0.192***	0.197***
	(0.0560)	(0.0551)	(0.0555)	(0.0551)	(0.0575)
diffmean	-2.714***	-2.675***	-2.641***	-2.694***	-3.947***
	(0.686)	(0.677)	(0.671)	(0.681)	(0.644)
diffafter	-0.681	-0.791*	-0.757	-0.803*	-0.764
	(0.469)	(0.461)	(0.461)	(0.461)	(0.481)
bapercentmaxmean	-1.906***	-1.882***	-1.914***	-1.857***	-1.782***
	(0.471)	(0.458)	(0.464)	(0.453)	(0.473)
impvolmean	0.170	-0.0354**			
	(0.154)	(0.0173)			
impvolstd	-0.0371	0.0254			
	(0.182)	(0.0224)			
impvolminmean	-0.0847		-0.0345**		
	(0.0605)		(0.0164)		
impvolminstd	0.0178		0.0207		
	(0.0862)		(0.0265)		
impvolmaxmean	-0.123			-0.0284*	-0.0223
	(0.0975)			(0.0152)	(0.0158)
impvolmaxstd	0.0499			0.0198	-0.00741
	(0.113)			(0.0185)	(0.0181)
Constant	1.200***	1.170***	1.119***	1.151***	1.173***
	(0.199)	(0.172)	(0.156)	(0.171)	(0.179)
Observations	204	204	204	204	204
R Squared	0.391	0.382	0.383	0.381	0.320
Adjusted R Squared	0.353	0.357	0.358	0.355	0.296

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11

Variable	diffmean
beta	-0.0139**
	(0.00611)
impcorrstd	-0.214***
	(0.0579)
rcorrstd	0.343***
	(0.0453)
impcorrmean	-0.0102
	(0.0239)
rcorrmean	0.0122
	(0.0244)
diffafter	0.135***
	(0.0384)
diffstd	0.671***
	(0.0617)
percentofobsimp	-0.00555
	(0.0128)
bapercentmean	-0.0375
	(0.303)
bapercentstd	1.323
	(0.955)
bapercentminmean	-0.0506
	(0.216)
bapercentminstd	-0.538
	(0.698)
bapercentmaxmean	-0.0793
	(0.145)
bapercentmaxstd	-0.278
	(0.320)
impvolmean	0.0210
	(0.0144)
impvolstd	-0.0300*
	(0.0167)
impvolminmean	-0.00936
	(0.00571)
impvolminstd	0.0169**
	(0.00758)
impvolmaxmean	-0.0137
	(0.00915)
impvolmaxstd	0.0165
	(0.0106)
Constant	0.0458**
	(0.0198)
Observations	192
R-squared	0.827
Adjusted R-Squared	.807

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Excludes Data from First Trimester Period

Table 12

Variable	diffmean	diffmean
beta	-0.0132**	-0.0135**
	(0.00563)	(0.00547)
impcorrstd	-0.156***	-0.156***
	(0.0441)	(0.0439)
rcorrstd	0.307***	0.307***
	(0.0416)	(0.0407)
impcorrmean	-0.0117	
	(0.0226)	
rcorrmean	0.0119	
	(0.0230)	
diffafter	0.124***	0.129***
	(0.0350)	(0.0336)
diffstd	0.658***	0.652***
	(0.0527)	(0.0511)
Constant	0.0241***	0.0248***
	(0.00822)	(0.00803)
Observations	192	192
R-squared	0.813	0.813
Adjusted R-Squared	.806	.808

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 13

Variable	diffmean	diffmean	diffmean	diffmean
beta	-0.0150**	-0.0146***	-0.0154***	-0.0126**
	(0.00584)	(0.00561)	(0.00561)	(0.00554)
impcorrstd	-0.189***	-0.188***	-0.172***	-0.161***
	(0.0525)	(0.0464)	(0.0454)	(0.0443)
rcorrstd	0.326***	0.320***	0.313***	0.310***
	(0.0419)	(0.0409)	(0.0407)	(0.0408)
diffafter	0.143***	0.148***	0.139***	0.132***
	(0.0371)	(0.0347)	(0.0343)	(0.0338)
diffstd	0.650***	0.654***	0.656***	0.651***
	(0.0551)	(0.0508)	(0.0510)	(0.0511)
percentofobsimp	-0.00219			
	(0.0104)			
bapercentmean	0.132	-0.121*	-0.0882	
	(0.289)	(0.0664)	(0.0630)	
bapercentstd	0.556	0.324		0.196
	(0.813)	(0.214)		(0.204)
bapercentminmean	-0.0299			
	(0.209)			
bapercentminstd	-0.463			
	(0.639)			
bapercentmaxmean	-0.148			
	(0.140)			
bapercentmaxstd	-0.0280			
	(0.275)			
Constant	0.0329**	0.0292***	0.0337***	0.0200**
	(0.0132)	(0.0106)	(0.0102)	(0.00942)
Observations	192	192	192	192
R-squared	0.819	0.817	0.815	0.814
Adjusted R-Squared	.807	.810	.809	.808

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 14

Variable	diffmean	diffmean	diffmean	diffmean	diffmean	diffmean
beta	-0.0141**	-0.0155***	-0.0144**	-0.0161***	-0.0128**	-0.0156***
	(0.00560)	(0.00569)	(0.00554)	(0.00568)	(0.00551)	(0.00567)
impcorrstd	-0.180***	-0.177***	-0.176***	-0.175***	-0.156***	-0.181***
	(0.0497)	(0.0483)	(0.0484)	(0.0455)	(0.0439)	(0.0455)
rcorrstd	0.309***	0.321***	0.308***	0.312***	0.312***	0.320***
	(0.0412)	(0.0411)	(0.0407)	(0.0406)	(0.0409)	(0.0409)
diffafter	0.141***	0.148***	0.141***	0.142***	0.131***	0.150***
	(0.0368)	(0.0358)	(0.0358)	(0.0346)	(0.0337)	(0.0349)
diffstd	0.664***	0.643***	0.662***	0.657***	0.645***	0.647***
	(0.0525)	(0.0529)	(0.0520)	(0.0509)	(0.0516)	(0.0512)
percentofobsimp	0.00644	-0.00243	0.00812			
	(0.00901)	(0.00996)	(0.00821)			
bapercentminmean	-0.0852					
	(0.164)					
bapercentminstd	0.103					
	(0.488)					
bapercentmaxmean		-0.0746*		-0.0552		-0.0686*
		(0.0440)		(0.0354)		(0.0364)
bapercentmaxstd		0.124			0.0803	0.117
		(0.0831)			(0.0766)	(0.0785)
Constant	0.0244**	0.0323**	0.0215**	0.0347***	0.0203**	0.0306***
	(0.0102)	(0.0127)	(0.00870)	(0.0102)	(0.00909)	(0.0106)
Observations	192	192	192	192	192	192
R-squared	0.814	0.818	0.814	0.816	0.814	0.818
Adjusted R-Squared	.806	.810	.808	.810	.808	.811

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 15

Variable	diffmean	diffmean	diffmean	diffmean
beta	-0.0156***	-0.0147***	-0.0154***	-0.0156***
	(0.00576)	(0.00562)	(0.00568)	(0.00567)
impcorrstd	-0.187***	-0.175***	-0.192***	-0.181***
	(0.0506)	(0.0453)	(0.0465)	(0.0455)
rcorrstd	0.319***	0.320***	0.318***	0.320***
	(0.0411)	(0.0410)	(0.0407)	(0.0409)
diffafter	0.152***	0.144***	0.152***	0.150***
	(0.0353)	(0.0345)	(0.0351)	(0.0349)
diffstd	0.651***	0.647***	0.655***	0.647***
	(0.0539)	(0.0514)	(0.0508)	(0.0512)
bapercentmean	0.0305	-0.101		
	(0.215)	(0.0637)		
bapercentstd	0.191		0.333	
	(0.640)		(0.214)	
bapercentmaxmean	-0.0883		-0.0739**	-0.0686*
	(0.114)		(0.0372)	(0.0364)
bapercentmaxstd	0.0560	0.100		0.117
	(0.239)	(0.0773)		(0.0785)
Constant	0.0299***	0.0295***	0.0301***	0.0306***
	(0.0108)	(0.0107)	(0.0106)	(0.0106)
Observations	192	192	192	192
R-squared	0.818	0.817	0.818	0.818
Adjusted R-Squared	.809	.810	.811	.811

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 16

Variable	diffmean	diffmean	diffmean	diffmean	diffmean
beta	-0.0149***	-0.0153***	-0.0151***	-0.0155***	-0.0155***
	(0.00570)	(0.00568)	(0.00569)	(0.00568)	(0.00567)
impcorrstd	-0.195***	-0.181***	-0.200***	-0.179***	-0.169***
	(0.0539)	(0.0530)	(0.0530)	(0.0528)	(0.0495)
rcorrstd	0.329***	0.331***	0.330***	0.330***	0.328***
	(0.0422)	(0.0417)	(0.0417)	(0.0415)	(0.0413)
diffafter	0.148***	0.149***	0.152***	0.149***	0.149***
	(0.0355)	(0.0352)	(0.0352)	(0.0352)	(0.0351)
diffstd	0.660***	0.641***	0.654***	0.640***	0.634***
	(0.0559)	(0.0540)	(0.0542)	(0.0544)	(0.0532)
bapercentstd	0.415*	0.352	0.287	0.371*	0.392*
	(0.231)	(0.225)	(0.224)	(0.222)	(0.218)
bapercentmaxmean	-0.0791*	-0.0811*	-0.0700*	-0.0812**	-0.0876**
	(0.0415)	(0.0411)	(0.0414)	(0.0404)	(0.0386)
impvolmean	0.0143	-0.00180			
	(0.0125)	(0.00169)			
impvolstd	-0.0268*	0.00105			
	(0.0151)	(0.00227)			
impvolminmean	-0.00655		-0.00190		
	(0.00511)		(0.00155)		
impvolminstd	0.0152**		0.00210		
	(0.00714)		(0.00251)		
impvolmaxmean	-0.00925			-0.00160	-0.000904
	(0.00775)			(0.00145)	(0.000697)
impvolmaxstd	0.0140			0.00100	
	(0.00923)			(0.00183)	
Constant	0.0362**	0.0435***	0.0391***	0.0436***	0.0394***
	(0.0175)	(0.0150)	(0.0136)	(0.0150)	(0.0128)
Observations	192	192	192	192	192
R-squared	0.824	0.820	0.819	0.820	0.820
Adjusted R-Squared	.812	.811	.810	.811	.812

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Excludes Data from First Trimester Period

Table 17

VARIABLES	diffmean
beta	-0.0171***
	(0.00559)
impcorrstd	-0.190***
	(0.0556)
rcorrstd	0.352***
	(0.0438)
impcorrmean	-0.00444
	(0.0236)
rcorrmean	0.00854
	(0.0242)
diffafter	0.114***
	(0.0383)
diffstd	0.661***
	(0.0602)
percentofobsimp	-0.00193
	(0.0118)
bapercentmean	-0.00226
	(0.304)
bapercentstd	1.460
	(0.953)
bapercentminmean	0.000938
	(0.216)
bapercentminstd	-0.732
	(0.660)
bapercentmaxmean	-0.0976
	(0.144)
bapercentmaxstd	-0.337
	(0.314)
impvolmean	0.0163
	(0.0142)
impvolstd	-0.0252
	(0.0166)
impvolminmean	-0.00560
	(0.00536)
impvolminstd	0.0125*
	(0.00709)
impvolmaxmean	-0.0117
	(0.00910)
impvolmaxstd	0.0142
	(0.0105)
Constant	0.0422**
	(0.0190)
Observations	204
R-squared	0.818
Adjusted R- Squared	.789

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 18

VARIABLES	diffmean	diffmean
beta	-0.0158***	-0.0154***
	(0.00519)	(0.00507)
impcorrstd	-0.154***	-0.153***
	(0.0431)	(0.0429)
rcorrstd	0.325***	0.321***
	(0.0407)	(0.0397)
impcorrmean	-0.00883	
	(0.0224)	
rcorrmean	0.0114	
	(0.0228)	
diffafter	0.106***	0.109***
	(0.0348)	(0.0333)
diffstd	0.656***	0.654***
	(0.0521)	(0.0505)
Constant	0.0230***	0.0241***
	(0.00798)	(0.00781)
Observations	204	204
R-squared	0.807	0.807
Adjusted R- Squared	.800	.802

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 19

VARIABLES	diffmean	diffmean	diffmean	diffmean
beta	-0.0165***	-0.0162***	-0.0166***	-0.0150***
	(0.00536)	(0.00516)	(0.00516)	(0.00511)
impcorrstd	-0.174***	-0.177***	-0.166***	-0.158***
	(0.0509)	(0.0451)	(0.0441)	(0.0434)
rcorrstd	0.336***	0.329***	0.324***	0.323***
	(0.0408)	(0.0400)	(0.0398)	(0.0399)
diffafter	0.117***	0.124***	0.118***	0.111***
	(0.0366)	(0.0344)	(0.0341)	(0.0334)
diffstd	0.648***	0.655***	0.656***	0.652***
	(0.0540)	(0.0505)	(0.0505)	(0.0506)
percentofobsimp	-0.00308			
	(0.00953)			
bapercentmean	0.133	-0.0940	-0.0727	
	(0.290)	(0.0636)	(0.0610)	
bapercentstd	0.639	0.237		0.150
	(0.795)	(0.205)		(0.197)
bapercentminmean	0.0267			
	(0.203)			
bapercentminstd	-0.676			
	(0.587)			
bapercentmaxmean	-0.146			
	(0.139)			
bapercentmaxstd	-0.0757			
	(0.265)			
Constant	0.0323***	0.0278***	0.0311***	0.0207**
	(0.0120)	(0.0102)	(0.00975)	(0.00899)
Observations	204	204	204	204
R-squared	0.812	0.809	0.808	0.807
Adjusted R- Squared	.800	.803	.802	.801

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 20

VARIABLES	diffmean	diffmean	diffmean	diffmean	diffmean	diffmean
beta	-0.0160***	-0.0168***	-0.0161***	-0.0171***	-0.0151***	-0.0169***
	(0.00521)	(0.00524)	(0.00516)	(0.00520)	(0.00509)	(0.00520)
impcorrstd	-0.167***	-0.168***	-0.167***	-0.168***	-0.154***	-0.172***
	(0.0486)	(0.0470)	(0.0470)	(0.0442)	(0.0429)	(0.0443)
rcorrstd	0.323***	0.329***	0.321***	0.324***	0.324***	0.329***
	(0.0402)	(0.0401)	(0.0398)	(0.0397)	(0.0400)	(0.0399)
diffafter	0.115***	0.124***	0.117***	0.121***	0.111***	0.126***
	(0.0363)	(0.0355)	(0.0353)	(0.0344)	(0.0334)	(0.0346)
diffstd	0.660***	0.647***	0.660***	0.657***	0.648***	0.650***
	(0.0519)	(0.0522)	(0.0514)	(0.0504)	(0.0510)	(0.0508)
percentofobsimp	0.00518	-0.00231	0.00557			
	(0.00835)	(0.00923)	(0.00791)			
bapercentminmean	-0.0355					
	(0.150)					
bapercentminstd	-0.0844					
	(0.455)					
bapercentmaxmean		-0.0604		-0.0473		-0.0554
		(0.0404)		(0.0343)		(0.0350)
bapercentmaxstd		0.0899			0.0604	0.0839
		(0.0772)			(0.0720)	(0.0732)
Constant	0.0243**	0.0306***	0.0219***	0.0320***	0.0210**	0.0291***
	(0.00974)	(0.0116)	(0.00841)	(0.00970)	(0.00863)	(0.0100)
Observations	204	204	204	204	204	204
R-squared	0.807	0.810	0.807	0.808	0.807	0.810
Adjusted R- Squared	.800	.802	.801	.803	.801	.803

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 21

VARIABLES	diffmean	diffmean	diffmean	diffmean
beta	-0.0170***	-0.0163***	-0.0168***	-0.0169***
	(0.00528)	(0.00517)	(0.00520)	(0.00520)
impcorrstd	-0.176***	-0.168***	-0.180***	-0.172***
	(0.0492)	(0.0442)	(0.0452)	(0.0443)
rcorrstd	0.328***	0.329***	0.328***	0.329***
	(0.0402)	(0.0401)	(0.0398)	(0.0399)
diffafter	0.128***	0.121***	0.128***	0.126***
	(0.0351)	(0.0342)	(0.0348)	(0.0346)
diffstd	0.652***	0.650***	0.655***	0.650***
	(0.0531)	(0.0509)	(0.0504)	(0.0508)
bapercentmean	0.0655	-0.0795		
	(0.216)	(0.0614)		
bapercentstd	0.101		0.251	
	(0.640)		(0.205)	
bapercentmaxmean	-0.0924		-0.0602*	-0.0554
	(0.114)		(0.0359)	(0.0350)
bapercentmaxstd	0.0570	0.0710		0.0839
	(0.234)	(0.0723)		(0.0732)
Constant	0.0282***	0.0281***	0.0286***	0.0291***
	(0.0102)	(0.0102)	(0.0101)	(0.0100)
Observations	204	204	204	204
R-squared	0.810	0.809	0.810	0.810
Adjusted R- Squared	.801	.802	.803	.803

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 22

VARIABLES	diffmean	diffmean	diffmean	diffmean	diffmean
beta	-0.0168***	-0.0173***	-0.0171***	-0.0174***	-0.0172***
	(0.00527)	(0.00523)	(0.00525)	(0.00522)	(0.00519)
impcorrstd	-0.175***	-0.168***	-0.181***	-0.167***	-0.159***
	(0.0523)	(0.0510)	(0.0513)	(0.0509)	(0.0475)
rcorrstd	0.337***	0.339***	0.333***	0.340***	0.339***
	(0.0413)	(0.0408)	(0.0407)	(0.0406)	(0.0404)
diffafter	0.121***	0.125***	0.128***	0.125***	0.125***
	(0.0353)	(0.0349)	(0.0350)	(0.0349)	(0.0348)
diffstd	0.656***	0.640***	0.653***	0.639***	0.634***
	(0.0552)	(0.0531)	(0.0534)	(0.0534)	(0.0524)
bapercentstd	0.368*	0.288	0.245	0.305	0.313
	(0.220)	(0.211)	(0.212)	(0.210)	(0.209)
bapercentmaxmean	-0.0710*	-0.0753*	-0.0643	-0.0758**	-0.0775**
	(0.0397)	(0.0384)	(0.0391)	(0.0380)	(0.0377)
impvolmean	0.00736	-0.00133			
	(0.0121)	(0.00134)			
impvolstd	-0.0196	0.000353			
	(0.0146)	(0.00178)			
impvolminmean	-0.00215		-0.000721		
	(0.00467)		(0.00127)		
impvolminstd	0.0103		0.000498		
	(0.00675)		(0.00215)		
impvolmaxmean	-0.00613			-0.00144	-0.000993
	(0.00766)			(0.00117)	(0.000690)
impvolmaxstd	0.0106			0.000687	
	(0.00906)			(0.00145)	
Constant	0.0358**	0.0410***	0.0337**	0.0428***	0.0396***
	(0.0165)	(0.0146)	(0.0135)	(0.0144)	(0.0127)
Observations	204	204	204	204	204
R-squared	0.815	0.812	0.810	0.812	0.812
Adjusted R- Squared	.803	.803	.802	.803	.804

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1