B Volatility Appendix

The aggregate volatility risk explanation of the turnover effect relies on three empirical facts. First, the explanation assumes that firm-specific uncertainty comoves with aggregate volatility. Thus, the relatively positive response of high uncertainty firms to a further increase in firm-specific uncertainty during recessions implies their relatively positive response to increases in aggregate volatility, i.e., lower aggregate volatility risk. Second, the explanation assumes that firm-specific uncertainty of high turnover firms responds to changes in aggregate volatility at least as strongly as firm-specific uncertainty of low turnover firms. Third, using the FVIX factor in the tests of the aggregate volatility risk explanation of the turnover effect implicitly assumes that FVIX satisfies all necessary conditions for a valid ICAPM factor. In this appendix, I test these three necessary conditions for the aggregate volatility risk explanation of the turnover effect.

B.1 Firm-Specific Uncertainty and Aggregate Volatility

The necessary condition for the aggregate volatility risk explanation of the turnover effect is the tight positive time-series correlation between aggregate volatility and firm-specific uncertainty. The existence of such correlation does not infer that firm-specific shocks have a systematic component, which would contradict the definition of the term "firm-specific." Rather, it is the volatility of these shocks that has a systematic component. One possible theory behind this correlation is the operating leverage theory: in recessions, when aggregate volatility is high, firms are closer to the break-even point, and therefore, the same firm-specific shock would imply a greater variation in profits/returns.

Panels A and B of Table 1B report the slopes from the pairwise regressions of the average idiosyncratic volatility and average analyst disagreement on the NBER recession dummy (equal to one in the months marked by NBER as recessions, zero otherwise) and the three measures of volatility: the VIX index, the market volatility forecast from the TARCH(1,1) model, and the realized volatility defined as the sum of squared daily returns to the market index within each month.

[Table 1B goes around here]

The first row of Panel A (Panel B) reports the slopes from the regressions of the log average idiosyncratic volatility (analyst disagreement) on the leads and lags of the NBER recession dummy. The slopes show that for an average firm, the state of recession predicts higher volatility and disagreement for up to 12 months going forward. In recessions, average idiosyncratic volatility and average analyst disagreement increase by about 30%.

The next rows of Panel A (Panel B) show that higher aggregate volatility, be it the VIX index, the TARCH(1,1) market volatility forecast, or the realized volatility of the market index, predicts higher levels of idiosyncratic volatility (analyst disagreement), and vice versa. The regressions are in logs, so the numbers in Panels A and B are elasticities. The economic magnitude of the link between aggregate volatility and firm-specific uncertainty is significant: on average, an increase in aggregate volatility by 1% will increase current and future idiosyncratic volatility and analyst disagreement by 0.2–0.4%. This effect is economically sizeable, since VIX, for example, can easily double or even triple during a recession, which would imply that average idiosyncratic volatility or analyst disagreement will increase by up to 120%.

Table 1B confirms the main premise of my theory that aggregate volatility and firm-specific uncertainty tend to increase together. Therefore, as my theory suggests that high uncertainty firms (including high turnover firms), all else equal, will increase in value when firm-specific uncertainty increases, it also implies that high turnover firms will load more positively on the FVIX factor than other firms with comparable market betas.

B.2 Sensitivity of Firm-Specific Uncertainty to Aggregate Volatility Changes across Turnover Quintiles

While the tests with the FVIX factor (Tables 6–10) successfully test the hypothesis that, all else equal, high turnover firms respond more positively to increases in aggregate volatility, it will add to the plausibility of my theory to show that the sensitivity of firm-specific uncertainty to changes in aggregate volatility is higher, or at least not lower, for high turnover firms. My theory suggests (the formal proof is available upon request) that even if the sensitivity does not depend on turnover, the value of firms with high uncertainty/turnover will respond more when average firm-specific uncertainty increases (by the same amount for all firms).

Table 2B records the average sensitivities of firm-level idiosyncratic volatility (Panel A) and analyst disagreement (Panel B) on three measures of aggregate volatility: the VIX index, TARCH(1,1) forecast of market volatility, and realized market volatility. For each firm-month, Panel A runs the regression

$$log(IVol_t) = a + b \cdot log(X_t), \quad X_t \in \{VIX_t; TARCH_t;\ \sigma_t^2(MKT)\}, \tag{B-1}$$

and Panel B runs the regression

$$log(Disp_t) = a + b \cdot log(X_t), \quad X_t \in \{VIX_t; TARCH_t;\ \sigma_t^2(MKT)\} \tag{B-2}$$

using monthly firm-level observations from the previous 36 months.

[Table 2B goes around here]

Since the regression is performed in logs, Table 2B reveals that firm-specific uncertainty of high turnover firms increases more, in percentage terms, when aggregate volatility increases. Naturally, the difference in the sensitivities would be even more pronounced if one looks at the regression with raw, not log, variables, since high turnover firms have higher uncertainty (see Table 5), and the same percentage change in their uncertainty means a larger absolute change.

To sum up, higher turnover indeed implies higher sensitivity of firm-specific uncertainty to changes in aggregate volatility. Hence, under my theory, the reaction of higher turnover firms to increases in aggregate volatility is guaranteed to be more favorable than that of low turnover firms.

B.3 Is the FVIX Factor a Valid ICAPM Factor?

In order to be a valid ICAPM factor, the FVIX factor has to satisfy three conditions. First, it has to closely track the change in VIX, which is the state variable it mimics. Second and most important, FVIX has to earn a significant risk premium, both in raw returns and on a risk-adjusted basis. Since, by construction, the returns to FVIX tend to be positive when VIX increases, the risk premium of FVIX has to be negative, as FVIX represents an insurance against volatility increases. Third, as Chen (2002) suggests, the volatility risk factor should be able to predict future volatility and future business conditions.

Panel A of Table 3B tests the first two necessary conditions. The left part of Panel A reports that FVIX is positively and significantly correlated with the change in VIX (the correlation is 0.65, t-statistic 14.9). Hence, FVIX is successful in mapping the innovations in the state variable (VIX index) into the return space.

The right part of Panel A shows that the average raw returns to FVIX are -1.215% per month, t-statistic -3.44. The large and significant negative risk premium of FVIX indicates that investors care about insurance against aggregate volatility increases provided by FVIX and are willing to pay a significant amount for such insurance. The risk premium of FVIX also exists in risk-adjusted returns, showing that the existing risk factors do not capture aggregate volatility risk. The CAPM alpha of FVIX is -46 bp per month, t-statistic -3.86, and the Fama-French alpha of FVIX is -45.5 bp per month, t-statistic -3.26.

[Table 3B goes around here]

Panel B of Table 3B tests Chen's (2002) conjecture that returns to a valid volatility risk factor should predict future volatility. The problem with using FVIX returns in predictive regressions is that the FVIX factor is constructed using one full-sample factor-mimicking regression. Panel B of Table 3B temporarily redefines FVIX: in each month, I run a separate factor-mimicking regression, using only the information available in that month, and then use the coefficients from this regression to form the FVIX in the next month.[1]

The first row of Panel B runs the probit regressions of the NBER recession dummy (equal to one in the months marked by NBER as recessions, zero otherwise) on the leads and lags of the FVIX returns. The significant slopes for the lags in Panel B suggest that FVIX returns are useful in predicting recessions for up to 12 months ahead (the actual predictability is even stronger, since NBER announces recessions/expansions 12–18 months after they are over). The insignificant slopes for the leads of the FVIX return indicate that recessions cannot predict FVIX returns, consistent with the efficient market hypothesis.

The next three rows of Panel B look at the ability of FVIX returns to predict three

[1] All results in the paper are robust to using this version of FVIX.

measures of volatility: the VIX index, TARCH(1,1) forecast of market volatility, and realized market volatility. Panel B reveals that all three measures can be predicted by FVIX returns from three and six months ago. The strongest predictability can be observed in the regressions with the TARCH(1,1) expected market volatility on the right-hand side. One can also observe that all measures of volatility exhibit a strong contemporaneous relation with FVIX.

In sum, Table 3B shows that FVIX satisfies all necessary conditions for being a useful ICAPM factor. It earns a significant risk premium in raw and risk-adjusted returns, it correlates significantly with the variable it mimics (the change in VIX), and its returns can predict future business conditions and future market volatility.

TABLE 1B
Uncertainty and Business Cycle

Panel A (Panel B) presents slopes from the regressions of the log average idiosyncratic volatility, IVol (analyst disagreement, Disp) on the business cycle variables. The business cycle variables are the NBER recession dummy, the log of the VIX index, the log market volatility forecast from the TARCH(1,1) model, and the log realized market volatility (detailed definitions are in Appendix A). The numbers in the top row are number of months by which I lag the business cycle in each column. The slopes indicate the percentage point increase in the average IVol (Disp) when either the NBER dummy changes from zero to one or any of the other variables increases by 1%. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Panel A. Average Idiosyncratic Volatility Predicted by Business Cycle Variables

	-12	-9	-6	-3	0	3	6	9	12
NBER	13.24	20.04	23.89	27.84	30.13	22.75	14.35	-0.71	-10.357
t-stat.	*1.64*	*2.08*	*2.63*	*3.47*	*3.91*	*2.67*	*1.50*	*-0.07*	*-1.00*
VIX	0.124	0.175	0.210	0.266	0.346	0.255	0.177	0.144	0.106
t-stat.	*1.50*	*2.19*	*2.71*	*3.44*	*4.54*	*3.17*	*2.21*	*1.81*	*1.30*
TARCH	0.002	0.063	0.147	0.263	0.420	0.369	0.286	0.238	0.176
t-stat.	*0.02*	*0.63*	*1.36*	*2.33*	*3.80*	*3.16*	*2.31*	*1.99*	*1.49*
Realized	0.080	0.120	0.152	0.199	0.278	0.178	0.117	0.082	0.047
t-stat.	*1.41*	*2.08*	*2.65*	*3.42*	*4.71*	*2.87*	*2.02*	*1.47*	*0.80*

Panel B. Average Analyst Disagreement Predicted by Business Cycle Variables

NBER	33.07	31.87	31.27	33.41	30.57	17.75	4.543	0.136	0.299
t-stat.	*2.89*	*3.13*	*3.03*	*3.23*	*3.38*	*2.73*	*0.54*	*0.01*	*0.04*
VIX	0.227	0.265	0.349	0.327	0.304	0.292	0.271	0.233	0.221
t-stat.	*3.90*	*4.40*	*4.54*	*4.32*	*4.53*	*4.85*	*4.80*	*3.68*	*3.39*
TARCH	0.239	0.321	0.433	0.447	0.442	0.441	0.400	0.352	0.342
t-stat.	*2.83*	*3.74*	*4.12*	*4.16*	*4.35*	*4.52*	*4.80*	*4.35*	*3.84*
Realized	0.185	0.196	0.247	0.224	0.217	0.171	0.154	0.145	0.160
t-stat.	*4.48*	*4.15*	*3.69*	*3.71*	*4.02*	*3.96*	*3.65*	*3.11*	*3.39*

TABLE 2B
Cross-Section of Uncertainty Sensitivity

Panel A (B) reports, for each turnover quintile, average slopes from regressions of log idiosyncratic volatility (log analyst disagreement) on log measures of aggregate volatility: VIX index, TARCH(1,1) forecast of market volatility, and realized market volatility (see Appendix A for definitions). The regressions are performed at the firm level using monthly data from the past 36 months. Each aggregate volatility measure is used separately. The turnover quintiles are based on average turnover in the previous quarter and use NYSE breakpoints. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Panel A. Average Log Sensitivity of Idiosyncratic Volatility

	Low	Turn2	Turn3	Turn4	High	L-H
VIX	0.276	0.352	0.368	0.371	0.357	0.082
t-stat.	5.55	8.16	8.66	9.07	9.65	3.86
TARCH	0.132	0.164	0.168	0.174	0.163	0.031
t-stat.	3.83	6.13	6.05	6.18	6.00	2.38
Realized	0.109	0.130	0.133	0.132	0.127	0.018
t-stat.	9.73	12.0	12.0	12.1	11.8	3.36

Panel B. Average Log Sensitivity of Analyst Disagreement

	Low	Turn2	Turn3	Turn4	High	L-H
VIX	0.059	0.054	0.073	0.088	0.140	0.081
t-stat.	2.64	2.48	3.20	4.06	4.63	4.48
TARCH	0.020	0.006	0.015	0.024	0.057	0.038
t-stat.	0.87	0.26	0.60	1.03	2.26	2.64
Realized	0.024	0.021	0.029	0.033	0.043	0.020
t-stat.	3.82	3.49	4.92	5.47	5.11	3.64

TABLE 3B
FVIX Factor as an ICAPM Factor

Panel A reports the correlations between FVIX and the VIX and its change on the left, and the alphas and Fama-French betas of the FVIX factor on the left. The FVIX factor is the fitted value less the constant from the regression of daily changes in the VIX index on the daily excess returns to the 2-by-3 sorts on size and book-to-market. The returns of the FVIX factor are cumulated to the monthly level. Panel B presents the slopes from the regressions of the business cycle variables on the FVIX factor returns. The business cycle variables are the NBER recession dummy, the log of the VIX index, the log market volatility forecast from the TARCH(1,1) model, and the log realized market volatility (detailed definitions are in Appendix A). The regression with the NBER dummy is probit regression. The numbers in the top row are number of months by which I lag the FVIX factor returns in each column. The slopes (with the exception of the probit regression) indicate the change in the business cycle variables (in percentage points) in response to 1% return to the FVIX factor. The t-statistics use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2010.

Panel A. FVIX as Factor-Mimicking Portfolio

	Correlations				FVIX Factor		
	FVIX	ΔVIX	VIX		Raw	CAPM	FF
FVIX	1	0.653	0.352	α	-1.215	-0.461	-0.455
t-stat.		*14.9*	*6.49*	t-stat.	*-3.44*	*-3.86*	*-3.26*
ΔVIX	0.653	1	0.288	β_{MKT}		-1.330	-1.368
t-stat.	*14.9*		*5.19*	t-stat.		*-29.5*	*-26.9*
VIX	0.352	0.288	1	β_{SMB}			0.201
t-stat.	*6.49*	*5.19*		t-stat.			*5.32*
				β_{HML}			-0.030
				t-stat.			*-0.49*

Panel B. Business Cycle Variables Predicted by FVIX Factor Returns

	-12	-9	-6	-3	0	3	6	9	12
NBER	2.846	2.825	3.983	4.027	1.940	-0.121	-0.697	0.194	0.817
t-stat.	*1.92*	*1.94*	*2.81*	*2.91*	*1.41*	*-0.08*	*-0.47*	*0.13*	*0.58*
VIX	0.109	0.308	0.457	0.649	1.620	-0.237	-0.157	0.013	-0.062
t-stat.	*0.39*	*0.99*	*1.47*	*1.87*	*4.49*	*-0.73*	*-0.44*	*0.04*	*-0.26*
TARCH	0.370	0.415	0.603	0.860	0.891	-0.206	-0.175	0.013	-0.004
t-stat.	*1.51*	*1.50*	*2.33*	*3.08*	*2.92*	*-0.78*	*-0.67*	*0.05*	*-0.02*
Realized	0.269	0.439	0.724	0.760	2.166	-0.004	-0.183	-0.007	0.071
t-stat.	*0.68*	*0.88*	*1.74*	*1.48*	*3.80*	*-0.01*	*-0.34*	*-0.02*	*0.19*