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Reference:
Verdickt Gertjan.- Is fertility a leading indicator for stock returns?
Finance research letters - ISSN 1544-6123 - 33(2020), UNSP 101203
Full text (Publisher's DOI): https://doi.org/10.1016/J.FRL.2019.06.001
To cite this reference: https://hdl.handle.net/10067/1608190151162165141

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Is fertility a leading indicator for stock returns?

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Abstract

If fertility behavior is closely related to business cycle behavior, there should be evidence in financial markets. I document that a decrease in fertility growth negatively forecasts real excess returns, several months ahead. More interestingly, this effect is not yet captured by demographic, business cycle or confidence metrics. The relationship is robust in specific subsamples. Overall, this suggests that fertility growth is a leading indicator for recessions.

Highlights

- Aggregate fertility growth negatively forecasts excess returns 18 months ahead.
- This relationship is not captured by other demographic changes.
- There is modest significance for specific subsamples.
- I fail to find a convincing explanation for this apparent relationship.

Keywords

Fertility growth, business cycle, recession, return predictability

JEL classification

G12, G17, J11, J13

I acknowledge the helpful comments by Jan Annaert, Kasey Buckles, Marc Deloof, Benjamin Golez, Kris Hardies and Leentje Moortgat, and the seminar participants at the University of Antwerp and University of Maastricht. Part of this research is conducted while I was a visiting researcher at Mendoza College of Business. I thank Amit Goyal to make the data available on his website.

Demographic trends are closely related to the state of the economy. A large literature documents the cyclical nature of fertility (e.g. Adserà and Menendez, 2011; Barro and Becker, 1989; Buckles et al., 2018; Hashimoto, 1974; Hotz et al., 1997). An explanation for this relationship is that people alter their behavior in response to an increase in unemployment rates. In asset-pricing literature, there is a strong focus on the ratio of middle-aged to young population. The changes in this ratio forecasts aggregate (Ang and Maddaloni, 2003) and cross-sectional returns (DellaVigna and Pollet, 2007). This variable captures the slow-moving part of dividend yield variation (Favero et al., 2011) and is positively correlated with stock market outflows (Goyal, 2004). Recently, Buckles, Hungerman and Lugauer (2018) show that conception rates begin to decrease several months before recessions. This suggests that fertility is more forward-looking than previously thought. If this assessment is correct, one should find a reflection of this behavior in financial markets.

Why would one expect to see evidence in financial markets? Stock prices decrease in a recession or, similarly, expected returns increase (Fama and French, 1989; Golez and Koudijs, 2018; Møller and Sander, 2017). If the decrease in fertility growth predicts recessions, several quarters ahead, than this decrease should also predict the increase in expected returns. Moreover, a decrease in stock prices can also be the result of a decrease in expected dividends (Campbell, 1991). In contrast to the literature, I use monthly live birth, hereafter referred to as fertility growth, rather than population data. If there are any predictable elements embedded in fertility growth, investors could use this information more quickly for asset allocation decisions (see Ang and Bekaert, 2004), among other applications.

1. Data

Prior research have showed that that the relationship between fertility and business cycle has changed during the 1970s. Multiple explanations have been proposed, such as, the increase in the use of anticonception, the women's participation in the workforce and labor market institutions (Adserà, 2004; Bailey, 2006; Buckles et al., 2018). Moreover, in the pre-1980 period, the aggregate number of live births in the United States is based on 'just' 50% of all live births. Between 1980 and 1985, a limited number of States provide 100% of live births. As of 1985, the data represents all monthly live births in the United States. For these reasons, and to increase comparability with Buckles et al. (2018), I begin the analysis in the 1988.

1.1. Fertility growth

Data on live births comes from the detail files of the National Center for Health Statistic's Natality. To address the seasonality in live births, I divide the number of live births in month *t* by month *t* of the previous year, as in[1]:

[1] In contrast to Buckles et al. (2018), I use monthly live births rather than conception rates since live births data are more easily accessible for economic agents. The National Center for Health Statistics publishes the number of live births on their website, whereas conception rates need to be calculated. If I lag the number of live births by nine months, which is a good approximation for conception rate, I get similar results (see Appendix).

$$FG_t = \frac{lb_t - lb_{t-12}}{lb_{t-12}} \quad (1)$$

where lb_t is the aggregate number of monthly live births in month t.

1.2. Stock market data

I apply real excess stock returns from CRSP database, with three-month Treasury bill rate as the risk-free rate. Dividend growth is computed as the monthly growth rate of the 12-month rolling sum of dividends to remove seasonality in the data.[2] In table 1, I find a modest positive correlation between dividend growth and fertility growth rate (0.22). A decrease in fertility growth is associated with a drop in dividend growth rate, which is an indication that there is a link between fertility and stock markets (Buckles et al., 2018). In turn, I document a low correlation between stock returns and fertility growth (0.02).

Table 1: Summary statistics

Panel A: Summary statistics

	Mean	Std. d.	Min	Max	AR(1)	Source
Fertility growth	0.000	0.027	-0.106	0.090	0.372	National Center for Health Statistics
< 20 year	-0.029	0.053	-0.160	0.095	0.882	National Center for Health Statistics
20 – 30 years	-0.006	0.030	-0.086	0.109	0.652	National Center for Health Statistics
30 – 40 years	0.017	0.029	-0.084	0.113	0.563	National Center for Health Statistics
No degree	-0.005	0.111	-0.459	0.455	0.914	National Center for Health Statistics
High school	0.016	0.084	-0.289	0.279	0.876	National Center for Health Statistics
College degree	0.019	0.113	-0.485	0.324	0.890	National Center for Health Statistics
White	-0.003	0.028	-0.091	0.096	0.561	National Center for Health Statistics
Black	0.002	0.036	-0.092	0.124	0.719	National Center for Health Statistics
Asian	0.085	0.194	-0.222	0.919	0.907	National Center for Health Statistics
Stock returns	0.005	0.041	-0.158	0.111	0.031	Amit Goyal
Dividend growth	0.003	0.007	-0.029	0.023	0.938	Amit Goyal
Recession	0.103	0.304	0	1	0.910	NBER
Dividend yield	-3.878	0.297	-4.528	-3.239	0.986	Amit Goyal
Earnings yield	-3.076	0.372	-4.841	-2.458	0.979	Amit Goyal
Consumer confidence	0.000	0.049	-0.199	0.220	-0.006	University of Michigan
Bullish	-0.005	0.109	-0.446	0.285	-0.358	AAII Investor Sentiment Survey
Bearish	-0.005	0.099	-0.438	0.315	-0.419	AAII Investor Sentiment Survey
Neutral	-0.003	0.070	-0.249	0.166	-0.402	AAII Investor Sentiment Survey
Divorces	-0.003	0.022	-0.055	0.044	-0.289	National Center for Health Statistics
Marriages	-0.012	0.041	-0.192	0.037	-0.089	National Center for Health Statistics
MY	0.006	0.027	-0.041	0.043	0.979	Census Bureau United States
CAY	1.011	0.177	0.704	1.688	0.315	Amit Goyal

Panel B: Correlation matrix

Panel B1: Monthly data

	Stock returns	Dividend growth	Dividend yield	Earnings yield	Consumer confidence	Neutral
Fertility growth	0.02	0.22	-0.06	0.22	0.06	-0.05
Stock returns	1	0.02	-0.03	0.00	0.16	-0.10
Dividend growth		1	-0.04	0.60	0.05	0.00
Dividend yield			1	0.30	0.01	0.00
Earnings yield				1	-0.06	0.01
Consumer confidence					1	0.10
Bullish						-0.43
Bearish						-0.23
Neutral						1

[2] Stock market data comes from Amit Goyal's website.

Panel B2: Annual data

	Stock returns	Dividend yield	MY	CAY	Marriages	Divorces
Fertility growth	-0.10	-0.01	-0.21	0.19	0.03	-0.28
Stock returns	1	-0.16	-0.20	-0.07	-0.13	0.15
Dividend yield		1	-0.38	0.25	-0.02	0.37
MY			1	0.11	0.02	-0.16
Cay				1	-0.17	-0.04
Marriages					1	0.15
Divorces						1

The table reports summary statistics (panel A) and correlation matrix (panel B) for all variables. The table covers the 1988-2017 period.

2. Empirical analysis

2.1. Methodology

To measure the extent to which fertility growth affect stock returns, I run the regression,

$$y_{t,t+h} = \alpha + \beta_1 FG_t + \beta_2 X_t + \varepsilon_{t+h} \tag{2}$$

where $y_{t,t+h}$ is the value-weighted cumulative log real excess returns or dividend growth rate from month t to $t+h$, FC_t is the log fertility growth rate in month t and X are control variables.[3]

2.2. Regression output

I report the regression output in real terms in table 2. In panel A, I show that a regression with fertility growth and the recession dummy as independent regressors do not yield any significant predictive relationship with future returns, up to 1 years ahead. However, at the 18-month horizon, I find a negative relationship between fertility growth and future returns at the 5% significance level) which becomes more significant at the 30- or 36-month horizon. More interestingly, this negative relationship remains robust in regression specifications. This result provides evidence to the hypothesis that an increase in fertility leads to a decrease in future excess returns.

In panel B, I report the results for the predictive regressions of fertility growth and expected dividend growth. I fail to find a significant relationship between these two variables. Return variation, followed by a change in fertility growth, is not explained by changes in expected cash-flows. I conclude that changes in discount rates, following a change in fertility growth, predominately explain future stock returns.

[3] I include multiple control variables in the online appendix, such as unemployment rate and economic policy uncertainty.

Table 2: Stock price dynamics

	h = 0	h = 1	h = 6	h = 12	h = 18	h = 24	h = 30	h = 36
Panel A: Returns								
Fertility growth rate	0.04	0.01	-0.20	-0.52	-0.89	-1.96***	-2.92***	-3.31***
	(0.47)	(0.08)	(-0.64)	(-1.15)	(-1.48)	(-2.80)	(-3.44)	(-3.50)
Dividend yield	0.00	0.01	0.09*	0.20***	0.31***	0.37***	0.41***	0.48***
	(0.20)	(1.32)	(1.93)	(2.35)	(2.46)	(2.31)	(2.49)	(2.93)
Earnings yield	-0.01	0.12	0.171	-0.23	-1.13	-0.36	0.77	1.28
	(-0.97)	(0.48)	(0.143)	(-0.13)	(-0.47)	(-0.21)	(0.24)	(0.380)
Recession	-0.03***	-0.02	-0.081	-0.17**	-0.18***	-0.14*	-0.10	-0.09
	(-2.24)	(-1.48)	(-1.241)	(-2.02)	(-2.54)	(-1.82)	(-1.42)	(-1.41)
AR²	0.02	0.02	0.10	0.20	0.24	0.27	0.33	0.38
Panel B: Dividend growth								
Fertility growth rate	0.02	0.01	0.02	-0.01	-0.18	-0.43	-0.80	-1.26*
	(1.175)	(0.34)	(0.30)	(-0.08)	(-0.65)	(-0.99)	(-1.42)	(-1.80)
Dividend yield	-0.01***	-0.00***	-0.04***	0.06***	-0.06	-0.05	-0.04	-0.04
	(-3.85)	(-4.98)	(-3.78)	(-2.28)	(-1.23)	(-0.71)	(-0.48)	(-0.38)
Earnings yield	0.01	0.01***	0.08***	0.13***	0.14***	0.13***	0.11	0.09
	(10.35)	(14.43)	(15.59)	(6.54)	(3.32)	(2.13)	(1.50)	(1.05)
Recession	-0.00	-0.00	-0.01***	-0.060***	-0.12***	-0.15***	-0.14*	-0.13*
	(-0.45)	(-0.38)	(-2.32)	(-2.65)	(-2.28)	(-2.17)	(-1.88)	(-1.66)
AR²	0.42	0.49	0.68	0.63	0.52	0.38	0.2	0.15

The table reports coefficients of the regression $y^i_{t,t+h} = \alpha^i + \beta_1 FG_t + \beta_2 X^i_t + \varepsilon^i_{t+k}$ where y^i_{t+h} is the value-weighted cumulative log real excess stock return (panel A) or log real dividend growth rate (panel B) over the period *t+h*, FG_t is the log fertility growth rate in month *t* and X are control variables, dividend and earnings yield; and NBER recession dummy. *T*-statistics are in parenthesis and estimated with Newey and West's (1987) standard errors to account for autocorrelation and heteroscedasticity, with the number of lags equal to the forecasting horizon. The table covers the 1988-2017 period. The data comes from the National Center for Health Statistics, NBER and Amit Goyal's website.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

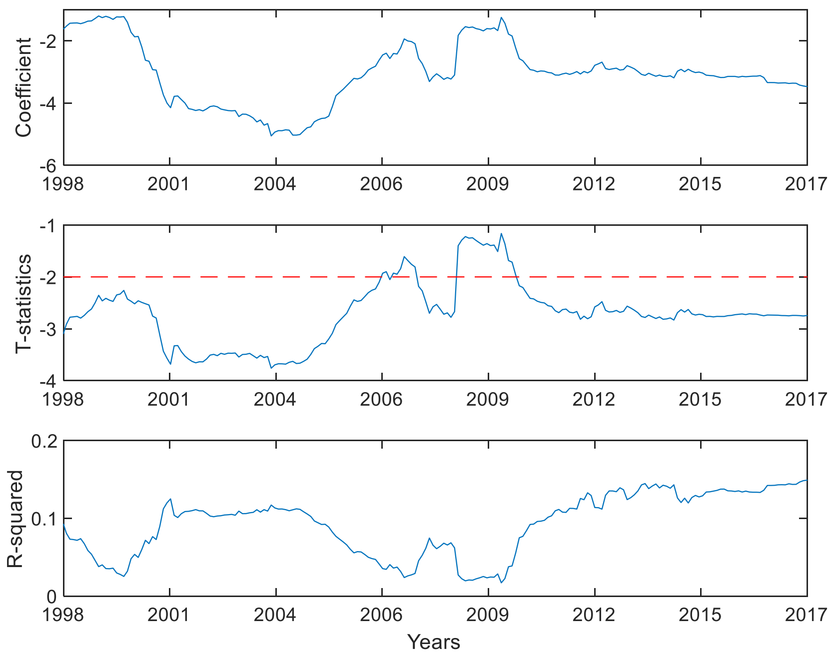
2.3. Rolling regressions

The instability of parameters is often mentioned as the major source of criticisms against return predictability evidence (Lettau and Van Nieuwerburgh, 2008; Paye and Timmermann, 2006). One possibility to account for this instability is through rolling regressions. I use 120 months as the rolling window, as in Chen (2009). Similar to in-sample regressions, I apply equation 1. Figure 1 (2) plots the return (dividend growth) regression for 24-months ahead.[4]

Figure 1 shows that the regression coefficients are relatively unstable through time. It varies between -1 and –5. More interestingly, in the middle panel, the *t*-statistics are almost always lower than the 95% confidence boundary (-1.96). There is a sharp increase around 2004, when the *t*-statistics is approximately -1.2. However, for the rest of the sample period, this relationship remains statistically significant. Therefore, I conclude that there is a strong negative relationship between fertility growth and future returns. I re-confirm the evidence from the in-sample regression model.

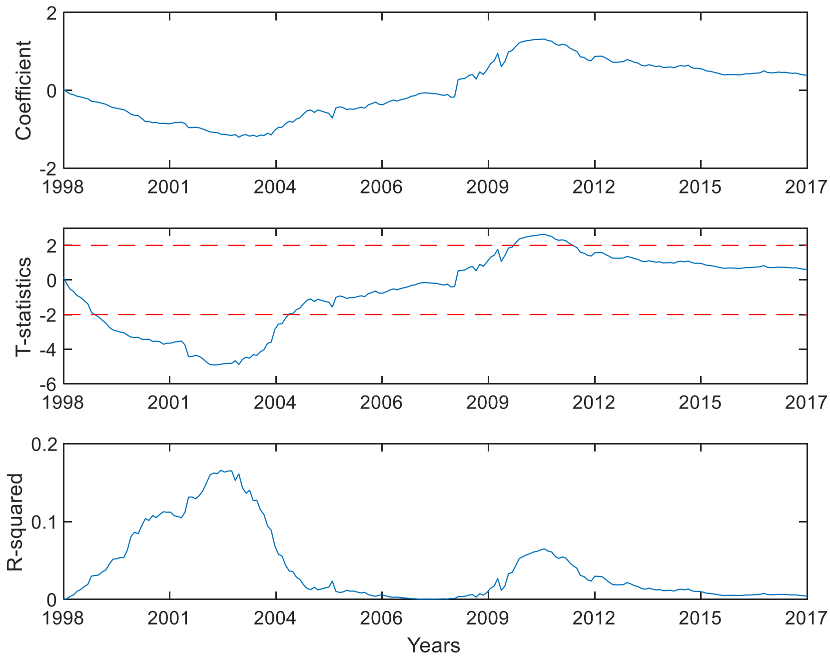
[4] Other time horizon are found in appendix.

Figure 1



This figure plots the 120-month rolling regression coefficients, Newey-West *t*-statistics (with 24 lags), and *R*-squared of returns on the 24-months lagged log fertility growth rate. The horizontal dashed line in the middle panel represents the 95% confidence boundary. The figure covers the 1998-2017 period.

Figure 2



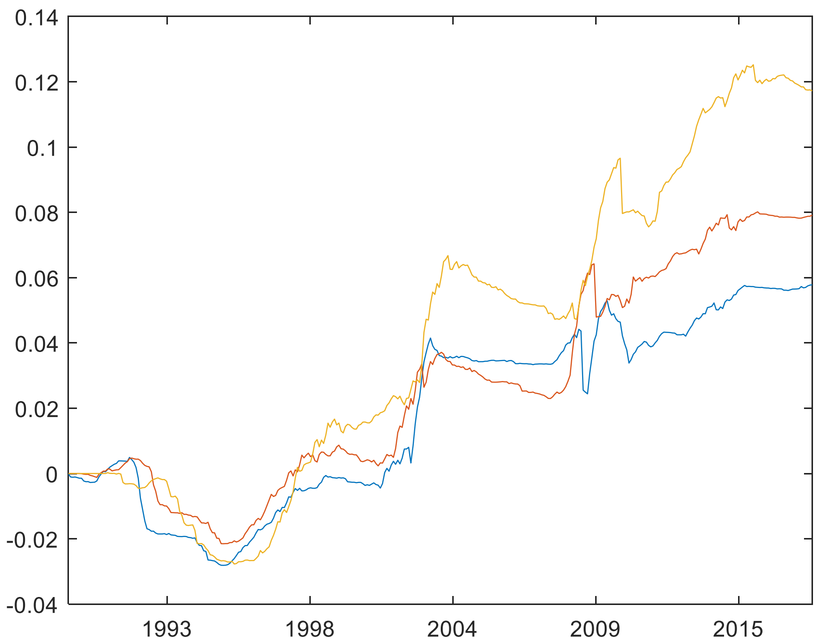
This figure plots the 120-month rolling regression coefficients, Newey-West t-statistics (with 24 lags), and R-squared of dividend growth on the 24-months lagged log fertility growth rate. The horizontal dashed lines in the middle panel represent 95% confidence boundaries. The figure covers the 1998-2017 period.

In addition, figure 2 shows that the dividend growth coefficient is also very unstable over time. The *t*-statistics very between -4 and 2, which are both significant at the 95% level. However, given the volatility of the metric, I fail to present evidence of the negative relationship between fertility growth and expected dividend growth. Hence, I re-confirm the evidence from the in-sample regression model. The variation in returns due to fertility growth is predominately explained by changes in discount rates rather than expected cash-flows.

I disentangle the R-squared evolutions in figure 3, as in Golez and Koudijs (2018). The lines plot the difference in the cumulative sum of squared errors between the constant-only model and a model with both a constant and fertility growth on expected returns. This difference is then normalized by the total sum of squared errors from the constant-only model. Each last observation represents the total in-sample R-squared. This figure is appealing since the lines indicate whether the fit of fertility growth on expected returns improves or declines.

I find that the regression models produce negative R-squared in the first 10 years, which means that constant-only models outperform models with fertility growth as the regressor. The in-sample R-squared comes mainly from 1998-2017 period. There are two spikes, around 2002 and 2009. Given that I use forecasting horizon of 18- to 36-months ahead, the spikes represent the start of two important financial crises (dot-cum bubble and the Great Recession). Therefore, I confirm the conclusions found in the in-sample and rolling regressions. The fertility behavior has some forward-looking components embedded (Buckles et al., 2018). A natural question, therefore, is why this is. I conduct additional tests in the following sections.

Figure 3



This figure shows differences in the cumulative sum of squared errors between a model with a constant only, and one with a constant, fertility growth rates and a NBER recession dummy. The difference is normalized by the total sum of squared errors from the constant-only model, so that the last observation corresponds to the in-sample R-squared for the 18-months (blue), 24-months (orange) and 36-months (yellow) ahead. The figure covers the 1988-2017 period.

3. Discussion

3.1. Subsamples?

There is a literature that documents differences for specific subsamples of the population and their behavior towards risk. For instance, van Rooij et al. (2011) find that people with a low level of financial literacy are less likely to buy stocks. Kumar (2009) documents that poor, young, less educated men of specific ethnicity groups (e.g. African-Americans) are more likely to buy lottery-type stocks, however they have fewer stocks in their portfolios. In light of the findings, I hypothesize that fertility growth rates for young, black and less educated women have a lower impact on stock returns. I focus on three subsamples, *Age*, *Race* and *Degree* – where I assume that *Degree* is a proxy for financial literacy (van Rooij et al., 2011). I focus on mothers' characteristics, since this has fewer missing observations than fathers.

Table 3: Stock price dynamics

	h = 0	h = 1	h = 6	h = 12	h = 18	h = 24	h = 30	h = 36
Panel A: Age								
< 20 year	-0.00	-0.03	-0.30*	-0.64**	-1.01***	-1.44***	-1.82***	-2.06***
	(-0.09)	(-0.83)	(-1.93)	(-2.13)	(-2.40)	(-2.36)	(-2.42)	(-2.57)
20 – 30 year	0.01	-0.03	-0.47*	-1.05***	-1.78***	-2.86***	-3.94***	-4.66***
	(0.13)	(-0.45)	(-1.94)	(2.40)	(-2.98)	(-3.07)	(-3.17)	(-3.48)
30 – 40 year	0.04	-0.01	-0.24	-0.53	-0.87*	-1.28***	-1.34*	-0.99
	(0.47)	(-0.12)	(-0.62)	(-1.07)	(-1.97)	(-2.86)	(-1.84)	(-1.07)
Panel B: Degree								
No degree	-0.00	-0.02	-0.16*	-0.32***	-0.43***	-0.46***	-0.54***	-0.61***
	(-0.07)	(-0.91)	(-1.83)	(-4.55)	(-4.02)	(-4.85)	(-3.08)	(-2.99)
High school	-0.01	-0.03	-0.24**	-0.51***	-0.72***	-0.72*	-0.75*	-0.82
	(-0.16)	(-0.98)	(-2.08)	(-2.97)	(-2.76)	(-1.75)	(-1.67)	(-1.57)
College degree	0.00	-0.01	-0.09	-0.14	-0.20	-0.10	0.00	0.01
	(0.04)	(-0.37)	(-0.74)	(-1.19)	(-1.35)	(-0.54)	(0.00)	(0.05)
Panel C: Race								
White	0.01	-0.05	-0.57**	-1.09***	-1.61***	-2.40***	-3.21***	-3.80***
	(0.12)	(-0.72)	(-2.03)	(-3.10)	(-4.29)	(-3.54)	(-3.15)	(-3.03)
Black	0.06	0.03	-0.22	-0.68*	-1.18***	-1.88***	-2.78***	-3.33***
	(1.05)	(0.51)	(-0.95)	(-1.72)	(-3.09)	(-3.31)	(-3.55)	(-3.65)
Asian	0.00	-0.00	0.01	-0.59	-0.10	-0.07	0.01	0.09
	(0.60)	(-0.26)	(0.13)	(-0.95)	(-1.14)	(-0.56)	(0.04)	(0.40)

The table reports coefficients of the regression $y^i_{t+h} = \alpha^i + \beta_1 FG_t + \varepsilon^i_{t+k}$ where y^i_{t+h} is the monthly value-weighted cumulated log real excess return over the period *t+h*, FG_t is the log fertility growth rate in month *t* based on the mother's age (panel A), degree (panel B) and race (panel C). *T*-statistics are in parenthesis and estimated with Newey and West's (1987) standard errors to account for autocorrelation and heteroscedasticity, with the number of lags equal to the forecasting horizon. The table covers the 1988-2017 period. The data comes from the National Center for Health Statistics Amit Goyal's website.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

I report the results in table 3. I show that for mothers aging below 20 and between 20 and 30, fertility growth negatively forecasts future excess returns. For mothers between 30 and 40, there is modest evidence of this predictive relationship. Hence, I confirm the evidence from previous literature. First, I show that the effect is smaller for younger women (below 20) compared to women aged 20 to 30 (Kumar, 2009). Second, I find that the effect is different for mothers aged 20 to 30 relative to 30 to 40 (Collin-Dufresne et al., 2017).

The negative trend is visible in the category *Degree*. The overall effect is larger in magnitude for mothers with high school degrees relative to mothers with no degree. However, fertility growth loses its predictive abilities for mothers with a college degree.

For *Race*, I find some forecasting ability for fertility growth rates on future excess returns for white and black mothers. The effect on stock returns is larger for *White* mothers, which confirms the findings of Kumar (2009). Asian mothers do not provide a similar pattern. However, on average, only 6% of women are in the category *Asian*, therefore, I do not put too much weight on this result. Overall, all results in table 3 suggests there is a significant negative relationship between fertility growth and future returns.

3.2. Marriage or divorce?

A topic that is closely related to fertility are marriages or divorces. In population economics, researchers have found a cyclical component in marriages and divorces (Eliason, 2012; Hellerstein et al., 2013; Schaller, 2013). An explanation is that, similar to fertility growth, an increase in unemployment rates is associated with a drop in marriage rates and divorce rates (Schaller, 2013). If the same dynamics drive fertility growth and marriage-divorce decision, regression coefficients should not yield statistically significant results. Given unemployment rates are a main force within both literatures, this is very likely the case.

In table 4, I report the results. Similar to demographic shift, the regression output is with an annual frequency. First, I document that the signs and magnitude of the fertility growth coefficient remains stable. As of 2 years ahead, there is a significant negative relationship between future returns and fertility growth. Second, I also show that changes in the number of divorces and marriages have little influence on future returns.

Table 4: Demographic control tests: marriages and divorces

	h = 1	h = 2	h = 3	h = 4
Fertility growth rate	-0.63	-5.91**	-7.15**	-7.66**
	(-0.48)	(-2.05)	(-2.12)	(-1.99)
Marriages	-1.31	1.56	0.68	1.66
	(-1.21)	(0.63)	(0.19)	(0.45)
Divorces	1.04***	0.99	0.91	1.31
	(3.22)	(0.86)	(1.53)	(0.77)
AR²	-0.02	0.15	0.11	0.21

The table reports coefficients of the regression $y^i_{t+h} = \alpha^i + \beta_1 FG_t + \beta_2 X^i_t + \varepsilon^i_{t+k}$ where y^i_{t+h} is the annual value-weighted cumulated log real excess stock returns over the period *t+h*, FG_t is the log fertility growth rate in month *t* and X are control variables, the log growth rate for marriages and divorces. *T*-statistics are in parenthesis and estimated with Newey and West's (1987) standard errors to account for autocorrelation and heteroscedasticity, with the number of lags equal to the forecasting horizon. The table covers the 1988-2016 period. The data comes from Amit Goyal's website and the United States Census Bureau.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

3.3. Demographic changes?

A strand in the asset-pricing literature focusses of the relationship between demographic changes and return predictability (Ang and Maddaloni, 2003; Collin-Dufresne et al., 2016; DellaVigna and Pollet, 2007; Favero et al., 2011). The focal point in this literature is *MY*. In table 5, I control for *MY* and *cay*. Since population statistics are only available on an annual basis, I use annual frequency in the empirical analysis, following Favero et al. (2011).

I report the regression results in table 5. I confirm the evidence found in monthly data. As of two years ahead, I document a negative predictive relationship between fertility growth and future returns. In all regression specifications, the relationship is significant at the 1% level. Hence, my conclusion holds with annual data and additional demographic variables.

Table 5: Demographic control tests

	h = 1	h = 2	h = 3	h = 4
Fertility growth rate	-0.56	-5.74***	-6.72***	-8.26***
	(-0.45)	(-2.19)	(-2.66)	(-2.64)
Dividend yield	0.27***	0.41***	0.62***	0.44***
	(2.73)	(2.98)	(4.96)	(3.20)
MY	0.26***	0.25	0.37**	0.20
	(2.76)	(1.39)	(1.98)	(1.17)
CAY	-0.64	-0.02	-0.33	1.17
	(-0.46)	(-0.01)	(-0.11)	(0.43)
AR^2	0.05	0.33	0.45	0.37

The table reports coefficients of the regression $y_{t+h}^{i} = \alpha^{i} + \beta_1 FG_t + \beta_2 X_t^{i} + \varepsilon_{t+k}^{i}$ where y_{t+h}^{i} is the annual value-weighted cumulated log real excess stock returns over the period *t+h*, FG_t is the log fertility growth rate in month t and X are control variables, log dividend yield, log middle-aged to young population (*MY*) and log consumption-to-wealth ratio (*CAY*). *T*-statistics are in parenthesis and estimated with Newey and West's (1987) standard errors to account for autocorrelation and heteroscedasticity, with the number of lags equal to the forecasting horizon. The table covers the 1988-2016 period. The data comes from Amit Goyal's website and the United States Census Bureau.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

3.4. Confidence?

Buckles et al. (2018) suggest that fertility behavior is more forward-looking than previously thought. If this is the case, fertility should be positively related to consumer confidence. In a perfect world, if people were able to foresee the future, fertility behavior and consumer confidence have a correlation of 1. Therefore, I include both variables in the regression analysis. If fertility behavior is related to consumer confidence, the regression coefficients will not remain significant. Similarly, I control for investor confidence since this exploits economic confidence (Cassella and Gulen, 2018).

In table 6, I find that the negative relationship between future returns and fertility growth holds for consumer (panel A) and investor confidence (panel B). An increase in fertility growth signals a decrease in future returns, as of 18-months ahead, at the 1% significance level. The findings suggest that the outlook of economic agents does not provide an explanation for the apparent relationship between fertility growth and future returns.

Table 6: Confidence control tests

	h = 0	h = 1	h = 6	h = 12	h = 18	h = 24	h = 30	h = 36
Panel A: Consumer confidence								
Fertility growth rate	0.02	0.01	-0.24	-0.66	-1.28***	-2.40***	-3.28***	-3.70***
	(0.18)	(0.15)	(-0.79)	(-1.45)	(-2.35)	(-3.34)	(-3.44)	(-3.46)
Consumer confidence	0.02***	0.01	0.00	0.23	0.30	0.29	0.32	0.29
	(3.07)	(0.22)	(0.04)	(1.09)	(1.39)	(1.35)	(1.54)	(1.47)
AR²	0.03	-0.01	-0.00	0.01	0.03	0.07	0.11	0.11
Panel B: Investor confidence								
Fertility growth rate	0.03	0.02	-0.23	-0.642	-1.26***	-2.41***	-3.31***	-3.75***
	(0.39)	(0.24)	(-0.74)	(-1.367)	(-2.23)	(-3.28)	(-3.34)	(-3.46)
Bearish	0.20	0.03	-0.31	0.02	0.52	0.82	1.45	1.72
	(1.54)	(0.22)	(-0.31)	(0.03)	(0.49)	(0.67)	(1.03)	(1.19)
Bullish	0.34***	0.03	-0.03	-0.00	0.51	0.78	1.40	1.65
	(2.68)	(0.24)	(-0.88)	(-0.00)	(0.50)	(0.65)	(1.01)	(1.16)
Neutral	0.25*	0.08	-0.87	-0.00	0.60	0.81	1.45	1.73
	(1.87)	(0.57)	(-0.31)	(-0.00)	(0.57)	(0.65)	(1.01)	(1.19)
AR²	0.13	-0.00	-0.01	0.01	0.02	0.07	0.11	0.12

The table reports coefficients of the regression $y^i_{t+h} = \alpha^i + \beta_1 FG_t + \beta_2 X^i_t + \varepsilon^i_{t+k}$ where y^i_{t+h} is the monthly value-weighted cumulated log real excess stock returns over the period *t+h*, FG_t is the log fertility growth rate in month *t* and X are control variables, log consumer confidence (panel A), and log bearish, bullish and neutral (panel B). *T*-statistics are in parenthesis and estimated with Newey and West's (1987) standard errors to account for autocorrelation and heteroscedasticity, with the number of lags equal to the forecasting horizon. The table covers the 1988-2017 period.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

4. Conclusion

Buckles, Hungerman and Lugauer (2018) provide an interesting finding: Fertility is more forward-looking than previously thought. If this assessment were true, there should be a reflection of this forward-looking behavior in stock markets. I find that fertility growth negatively forecasts excess returns as of 18 months ahead. I show that this relationship is driven by changes in discount rates rather than cash-flows news. More interestingly, I show that this effect is not driven by other demographic and confidence measures. Similar to Buckles et al. (2018), however, I fail to provide a solid explanation of this relationship. Since this research uses the standard methodology in the return predictability literature, I echo the conclusion from Novy-Marx (2014) not to reject these results instantly. Researchers could study this more in-depth, through the time-series or cross-section.

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