EXCHANGE RATES, FINANCIAL CONSTRAINTS, AND INVESTMENT IN THE U.S. MANUFACTURING SECTOR

By

Rex M. Ballinger

Submitted to the

Faculty of the College of Arts and Sciences

of American University

in Partial Fulfillment of

the Requirements for the Degree

of Doctor of Philosophy

In

Economics

Chair: Professor Robert A. Blecker

Professor Kara M. Reynolds

Professor Robert M. Feinberg

Dean of the College

November 25, 2013

Date

2013
American University
Washington, D.C. 20016

EXCHANGE RATES, FINANCIAL CONSTRAINTS,
AND INVESTMENT IN THE U.S.
MANUFACTURING SECTOR

by
Rex M. Ballinger

ABSTRACT

This dissertation investigates the impact of the real value of the dollar on investment in U.S. manufacturing using both industry-level and firm-level panel data. Although there is a large literature on investment functions, relatively few studies have estimated exchange rate effects on investment. This study begins by estimating models based on Campa and Goldberg (1999) with more recent industry-level data (for 1976-2005) and more advanced econometric methods. Their finding of a significant positive effect of dollar appreciation on investment through the channel of lower costs of imported inputs cannot be confirmed. However, there is robust evidence for negative effects of the real value of the dollar via the channel of export competitiveness for all industries and ones with high markup rates and import penetration. Alternative estimation techniques are used to correct for serial correlation, heteroskedasticity, and cross-sectional dependence, and as a robustness check for the results. Industry-specific, trade-weighted exchange rates are also used as another sensitivity test, and the results show significant negative coefficients on changes in the export-weighted real dollar index for the whole sample and three out of four industry subsamples.

This dissertation then provides estimates of the impact of the real exchange rate on investment at the firm level in U.S. manufacturing for 1995-2010, using a modified accelerator model that controls for the user cost of capital and financial (liquidity) constraints. The dissertation corrects biases in previous micro-level measures of user cost and shows that using chain-weighted user costs eliminates the endogeneity that is found with time-varying weights. Although the trade-weighted real dollar indexes are not significant in the entire sample, there are significant negative effects of dollar appreciation in subsamples defined by high degrees of export orientation, imported input use, import penetration, and all three combined, especially using the indexes weighted by total trade and by imports. Results for whether the dollar index is significant in levels or growth rates vary, indicating some ambiguity about whether the exchange rate affects desired capital stocks, liquidity constraints, or simply the rate at which firms adjust toward their desired capital stocks.

ACKNOWLEDGEMENTS

Most important, I would like to acknowledge the infinite patience of love. Nearly seven years ago to the day, my wife (who was two years into her own seven-year residency and fellowship training) went into labor with our first child. At the time, I was unreachable by phone, because I was in the basement of the Bender Library working on my first presentation of this topic. As a harbinger of the hardship we would face as a family during the writing of this dissertation, she drove herself to the hospital. Sixteen months later our second child was born, and for their entire lives, my boys have only known me as a struggling doctoral candidate. I can never thank my wife and sons enough for their love, support, and infinite patience — I am done!

I would like to thank my committee members, Robert Feinberg and Kara Reynolds, for their enduring support, help, and sage advice, especially in the surge to completion. Special thanks go to my chair, Robert Blecker, for providing the help and encouragement to get me through the direst of times. I would also like to thank Bob Chirinko, Steve Fazzari, Linda Goldberg, and Maria Spatareanu for answering questions from some unknown student, who kept pestering them with e-mails.

Last, I would like to thank all of my friends in the greater Washington, DC area for providing all manner of logistical support on my return visits (aiport rides, cars, beds, couches, etc.). More importantly, I would like to thank them for the camaraderie and comic relief they provided to help me persevere. I always cherish our time together, and I will miss my regular visits to DC.

TABLE OF CONTENTS

ABSTRACT ii

ACKNOWLEDGEMENTS iv

LIST OF TABLES vii

LIST OF FIGURES x

CHAPTER

1. INTRODUCTION 1

2. LITERATURE SURVEY AND THEORETICAL MODELS 5

2.1 Exchange Rates and Investment 5

2.1.1 Early Empirical Studies 6

2.1.2 Theoretical Model of Exchange Rates and Investment 8

2.1.3 Empirical Applications of the Campa-Goldberg Model 17

2.1.4 Aggregate and Cross-country Studies 19

2.1.5 Critical Review 20

2.2 General Literature on the Investment Function 22

2.2.1 Accelerator and User Cost Models 23

2.2.2 Models of Financial (or Liquidity) Constraints 25

2.2.3 Synthesis and Extensions 27

2.3 Conclusion 30

3. DATA 33

3.1 Industry Level Data 33

3.1.1 Replication 33

3.1.2 Extended Dataset 40

3.2 Firm Level Data 49

3.2.1 User Cost of Capital 49
3.2.2 Firm Data: Investment and Capital Stocks 57
3.2.3 Other Firm Level Data 61
3.2.4 Unit Root Tests 62
3.A Concordance for 2002 I-O Codes to 1987 SIC Codes 65
3.B Asset Codes 67
4. INDUSTRY LEVEL ESTIMATES 70
4.1 Replication 70
4.2 Extension 83
4.2.1 Non-i.i.d. Errors in Panel Data 84
4.2.2 Comparison of Econometric Methods 86
4.2.3 Industry Level Exchange Rates 102
4.3 Conclusion 106
4.A Sensitivity Tests 109
5. FIRM LEVEL ESTIMATES 119
5.1 Replication 119
5.2 Extension: Real Exchange Rates 140
5.2.1 Baseline Estimates for All Firms 140
5.2.2 Exchange Rate Exposure 145
5.2.3 Exposure by Export Share 147
5.2.4 Exposure by Imported Input Share 150
5.2.5 Exposure by Import Penetration 155
5.2.6 Overall Exchange Rate Exposure 159
5.3 Conclusion 163
6. CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH 167

REFERENCES 177

LIST OF TABLES

Table Page

3.1. Measures of External Exposure for U.S. Manufacturing Industries, 1985. Comparison to the Benchmark Study: (a) Actual Data, (b) Benchmark Data. 36

3.2. Ratio of Variances of Transitory Component to Actual Exchange Rate 39

3.3. Summary Statistics for the Markup Variable 45

3.4. Phillips-Perron Time Series Unit Root Tests, 1974-2005 47

3.5. Levin-Lin-Chu Panel Data Unit Root Tests, 1974-2005 48

3.6. Summary Statistics of the Industry-specific User Cost and the Asset-specific Components of the User Cost 52

3.7. Exchange Rate Series Unit Root Tests, 1974-2010 64

3.8. Fisher-type Panel Data Unit Root Tests, 1989-2010 65

3.9. Example of Concordance between 6-digit, 2002 I-O Code and 2-digit, 1987 SIC Code 66

3.10 Capital Assets Used in U.S. Manufacturing Industries 67

4.1. Replication of 3SLS: Equations Corrected for Serial Correlation 72

4.2. IV/GMM Estimation of Investment Equation 78

4.3. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Comparison between Nominal and Real Interest Rates, and between Permanent and Actual Exchange Rates. No Adjustment for Autocorrelation. 89

4.4. Sample Splits by Markup and Import Share 91

4.5. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Sample Splits by Markup and Import Competition. No Adjustment for Autocorrelation. 92

4.6. OLS with PCSE: Sample Splits by Markup and Import Competition. No Adjustment for Autocorrelation. 94

4.7. OLS with DKSE: Sample Splits by Markup and Import Competition. Robust to Sixth Order Autocorrelation. 96

4.8. FEGMM with DKSE: Sample Splits by Markup and Import Competition. Robust to Sixth Order Autocorrelation. Tests of Interest Rate Endogeneity. 97

4.9. OLS with DKSE: Modified Domestic Channel. 100

4.10. OLS with DKSE: Industry-specific, Total Trade Weighted Exchange Rates. 103

4.11. OLS with DKSE: Industry-specific, Import Weighted Exchange Rates. 104

4.12. OLS with DKSE: Industry-specific, Export Weighted Exchange Rates. 105

4.13. Replication of 3SLS: No Correction for Serial Correlation 109

4.16. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Sample Splits by Markup and Import Competition. Adjustment for Panel-specific $AR(1)$ Correlation. 110

4.14. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Comparison between Nominal and Real Interest Rates, and between Permanent and Actual Exchange Rates. Adjustment for panel-specific $AR(1)$. 111

4.15. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Comparison between Nominal and Real Interest Rates, and between Permanent and Actual Exchange Rates. Adjustment for Common $AR(1)$. 112

4.17. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Sample Splits by Markup and Import Competition. Adjustment for Common $AR(1)$ Correlation. 113

4.18. Prais-Winsten Estimation with PCSE: Sample Splits by Markup and Import Competition. Adjustment for Panel-specific $AR(1)$ Correlation. 114

4.19. Prais-Winsten Estimation with PCSE: Sample Splits by Markup and Import Competition. Adjustment for Common $AR(1)$ Correlation. 115

4.20. OLS with DKSE: Sample Splits by Markup and Import Competition. Robust to Third Order Autocorrelation. 116

4.21. OLS with DKSE: Sample Splits by Markup and Import Competition. No Adjustment for Autocorrelation. 117

4.22. FGLS: Industry-specific, Total Trade Weighted Exchange Rates. 118

4.23. OLS with PCSE: Industry-specific, Total Trade Weighted Exchange Rates. 118

5.1 OLS Regressions: Comparison to Chirinko et al. (1999) 120

5.2 OLS Mean Difference Regressions: Alternative User Cost Measures 123

5.3 OLS First Difference Regressions: Alternative User Cost Measures 125

5.4 IV Regression (Orthogonal Deviations): Alternative User Cost Measures 128

5.5 Difference GMM (Orthogonal Deviations): Alternative User Cost Measures 131

5.6 Robust Difference-GMM (Orthogonal Deviations): Alternative User Cost Measures . 135

5.7 Robust, Two-way Fixed Effects OLS 137

5.8 Two-way Fixed Effects OLS, with and without the Exchange Rate 142

5.9. Sample Splits by International Exposure, According to Primary Industry Classification. 145

5.10. Two-way FE OLS: High Export Share Industries 147

5.11. Two-way FE OLS: Low Export Share Industries 149

5.12. Two-way FE OLS: High Imported Input Share Industries 151

5.13. Two-way FE OLS: Low Imported Input Share Industries 153

5.14. Two-way FE OLS: High Import Penetration Industries 156

5.15. Two-way FE OLS: Low Import Penetration Industries 157

5.16. Two-way FE OLS: High Overall Exchange Rate Exposure 160

5.17. Two-way FE OLS: Low Overall Exchange Rate Exposure 162

LIST OF FIGURES

Figure | Page

3.1. Actual and Permanent Components of the Real, Broad Index of the Value of the U.S. Dollar: Annual Averages, 1973-2005 41

3.2. External Exposure by Industry, 1973-2005 44

3.3. Unweigted Averages of the Relative Price of Capital by Type of Asset, 1987-2010 . . 54

3.4. Weighted Averages of the Relative Price of Capital for All Assets, 1987-2010 55

CHAPTER 1

INTRODUCTION

Since the late 1990s, there has been a perceived "crisis" in the U.S. manufacturing sector. Some commentators have claimed that a vital part of the U.S. industrial base has been hollowed out (see *e.g.* Fingleton (1999) and Schonberger (2001)). From 1998 to 2010, U.S. manufacturing employment declined by over six million jobs,[1] and the manufacturing capital stock, which had risen steadily from 1970, began to level off.[2] The U.S. trade deficit in goods, which consists mostly in manufactures, increased from $337.4 billion in 1999 to $838.8 billion in 2006, and still stood at $741.5 billion in 2012.[3]

Around the same time, the broad, trade-weighted real value of the dollar was in the midst of a prolonged period of appreciation (from 1995 to 2002), which raised questions about whether there could be real and persistent effects of the exchange rate on the U.S. economy. The dramatic changes in the manufacturing sector noted above raised questions about the increased role of outsourcing, and whether a higher real value of the dollar encouraged offshore production of intermediate goods. Even after the dollar's peak in 2002, questions were still raised about the effects on U.S. manufacturing of currency manipulation by certain countries during a general period of depreciation for the broad measure of the dollar. Given the more globalized nature of the world economy, the question of whether domestic capital formation is significantly affected by the relative profitability or competitiveness of home and foreign production as reflected in the real exchange rate becomes a matter of great policy significance.

---

[1] U.S. manufacturing employment fell from 17.6 million jobs in March of 1998 to 11.5 million jobs in February of 2002 (BLS data series CES3000000001, `www.bls.gov`).

[2] The replacement value of the capital stock for manufacturing industries at year end in 1998 was $1.93 trillion in chain-weighted 2005 dollars and by 2010 it was only $1.98 trillion (BEA fixed asset tables, `www.bea.gov`).

[3] See U.S. Census Bureau, 2013, Annual trade in goods and services, `www.census.gov`.

A majority of the previous research on the investment-exchange rate relationship for the U.S. manufacturing sector has been focused at the industry level (Goldberg (1990, 1993) and Campa and Goldberg (1995, 1997, 1999)) and was conducted before the post-1995 dollar appreciation and subsequent depreciation, post-2002. In addition, this earlier research found conflicting results, with some studies finding that a dollar appreciation had a mostly negative effect on domestic investment and others finding mostly positive effects. The study of Campa and Goldberg (1999) has become the standard framework for open economy investment research, and it relies on identifying the channels of transmission for the exchange rate to affect the desired capital stock. The studies that relied on such a framework for the U.S. manufacturing sector, however, have used an outdated estimate of production technology that is based upon 1982 Input-Output tables and would not reflect the evolution in U.S. manufacturing production since. Moreover, these studies placed less emphasis on the role that the exchange rate has on the competitiveness of U.S. manufacturing industries *vis a vis* imported final goods and on a determination of the net effect on investment of a dollar appreciation or depreciation. On the one hand, it could be hypothesized that periods of an appreciating dollar contributed to the decline of the manufacturing sector at critical junctures in recent decades by making U.S. products less competitive in global markets. On the other hand, it might be thought that the globalization of production and the increased reliance of U.S. industries on imported intermediate goods have reversed the direction of the exchange rate's effect so that an appreciation could boost profitability and thereby increase desired investment by lowering the costs of such imported inputs.

When compared to the more general studies of investment functions, few of which included international variables, the theoretical framework of Campa and Goldberg (1999) and the resulting empirical work on the U.S. manufacturing sector does have certain limitations. Notably absent in the work of Campa and Goldberg (1999), but stressed in the broader investment function literature, are the longer term nature of capital formation, a broad measure of the cost of capital that accounts for changes in the relative prices of capital goods, and a consideration of financial/liquidity constraints on investment. Blecker (2007) attempted to overcome these issues in an aggregate study of the U.S. manufacturing sector. He found large negative effects of the real value of the dollar on investment, contrary to the conclusions of Campa and Goldberg (1999). However, Blecker did not use micro-level (industry or firm) data.

This study addresses the differing conclusions of Campa and Goldberg (1999) and Blecker (2007) by conducting two alternative analyses at the industry and firm levels of the effect of the exchange rate on investment in the U.S. manufacturing sector. First, in Chapter 2 I will present a critical survey of the literature on the effects of the exchange rate on domestic investment and attempt to bridge the gap between it and the more general literature on the investment function. I also provide thorough coverage of the standard theoretical framework used in the literature on the effect of the exchange rate on investment and compare it to frameworks more commonly used in the rest of the investment function literature. I also provide justification for my choice of different modelling frameworks for the two separate analyses.

In Chapter 3, I will provide a detailed discussion of the data used in each study. In order to extend the time period of the data used in the industry level analysis beyond that of Campa and Goldberg (1999), I rely on trade and manufacturing industry data that was rigorously concorded to the two-digit SIC level and that was not used in previous studies of investment. Furthermore, in order to update the estimate of U.S. manufacturing industries' production technology, I develop an equally rigorous concordance between the 2002 Benchmark Input-Output tables and the 1987 two-digit SIC scheme. I also provide a critical investigation into the assumptions used by Campa and Goldberg (1999) to determine permanent exchange rate changes, and I include a discussion as to how industry-specific exchange rates are preferrable for determining the net effect of exchange rate changes on investment. For the data used in the firm level analysis, I also create a new and revised data set that updates the period of investigation from previous studies of the investment function. Furthermore, I identify shortcomings in previous estimates of the user cost of capital that rely on the traditional method of time-varying weights. As I show in Chapter 3, this weighting scheme becomes problematic in the presence of rapidly declining prices for certain capital goods. I develop a fixed weighting scheme and a chain weighting scheme for the user cost of capital in order to address this problem.

In Chapter 4, I will apply the model of Campa and Goldberg (1999) to the new and revised data and correct for various problems I have identified in their econometric approach. I contribute to the literature by updating the measure of imported input reliance to reflect more recent input-output tables and extend the period of analysis to 2005. In addition, I take more careful account of the effect of the exchange rate on the competitiveness of domestic goods that face pressure from competing imports. I also seek to determine the overall net effect of the exchange rate on investment by using industry-specific exchange rates, which to my knowledge have not been used previously in either section of the investment literature. As will be discussed in depth in Chapter 4, I find that Campa and Goldberg (1999) probably corrected for the wrong violations of classical least squares assumptions, and I use newer methods of panel data estimation to correct for the violations that I find, which are chiefly cross-sectional dependence and heteroskedasticity.

In Chapter 5, I will provide the first analysis of the exchange rate on investment in the U.S. at the firm level. Using a more open-ended distributed lag model of investment, I will test empirically whether the exchange rate is more likely to affect the desired capital stock as found in Campa and Goldberg (1999), or whether it is more likely to affect the rate of investment through the channel of liquidity constraints as found in Blecker (2007). In addition, I will show that using a time-varying weighted measure of the user cost of capital creates unnecessary endogeneity, which can best be corrected using a chain-weighted measure. Lastly, in Chapter 6, I will provide a synthesis of the conclusions from each analysis and recommend a course for future research.

CHAPTER 2

LITERATURE SURVEY AND THEORETICAL MODELS

In this chapter, I survey two strands of the investment literature that for the most part have very little overlap. In the first section, I cover the relatively smaller set of literature on the effects of exchange rates on domestic investment in an open economy setting. This literature includes a now-standard model of exchange rate effects on investment that will serve as the foundation for the first set of empirical estimates in this dissertation. Next, I provide a brief overview of the much larger literature on investment functions in general, most of which has ignored open economy issues and has not tested for exchange rate effects. As will be explained below, this latter literature nevertheless constitutes an important foundation for alternative estimates of the impact of exchange rates on investment that properly control for the variables that have been proven to have the most success in explaining investment empirically. Last, I provide some concluding remarks and justify my use of these two alternative estimation frameworks in this study of exchange rate effects on investment.

2.1 Exchange Rates and Investment

When compared to the vast literature covering either the open economy or investment, the number of studies that investigate the linkages between the exchange rate and domestic investment is still relatively small. A majority of this research has used industry-level panel data to investigate the effect of the real exchange rate on investment, but others have extended this work to studies at the aggregate or firm level.

2.1.1 Early Empirical Studies

The initial foray into this subject matter was an empirical analysis by Worthington (1991). Using panel data methods on a simple model of annual, industry-level U.S. manufacturing investment from 1963 to 1986, Worthington (1991) found a significant, net negative effect of the real value of the dollar on the rate of investment after controlling for accelerator effects. Goldberg (1993) followed with an analysis using quarterly, industry-level investment in the U.S. from 1970 to 1989. In that analysis, she investigated the effects of both the real value of the dollar and its volatility on industry investment. She found that the effects of exchange rate volatility were generally small and/or insignificant. At various levels of aggregation for large sectors of the U.S. economy (including manufacturing), Goldberg (1993) found no evidence of a significant effect of the real exchange rate on investment for the full time period; however, she did find evidence of a significant, net positive effect of increases in the real value of the dollar on investment in durables industries for the sub-period 1979:3 to 1989:4. In addition, Goldberg (1993) found that significant exchange rate effects frequently arose in this sub-period when analyzing each industry separately, and the direction of the effect was dependent upon the industry. For the manufacturing durables sector, she found that the level of the real value of the dollar had a positive effect on investment in three of the industries, while it had a negative effect in three others. As a result, Goldberg (1993) concluded that aggregate analyses of the effect of the exchange rate on investment may mask the underlying industry-specific effects of the exchange rate on investment. On the other hand, Blecker (2007) suggested that Goldberg's failure to find more significant effects may have resulted from her use of contemporaneous quarterly data without any lags, which did not account for the longer term nature of business fixed investment.

In these two early studies, Worthington (1991) and Goldberg (1993) set out to provide largely empirical investigations into the question of what is the overall effect of the exchange rate on investment. Both authors recognized that a higher real value of the dollar could discourage domestic investment by reducing the competitiveness of U.S. goods in export markets, yet it also could encourage investment due to the lower cost of imported intermediate goods. Neither study gave much, if any, attention to the role of the exchange rate on the competitiveness of industries within the domestic market due to competition with imported final goods.

Campa and Goldberg (1995) combined the work of Goldberg (1993) with her earlier study (Goldberg, 1990) of international exchange rate exposure and measures of external orientation.

Campa and Goldberg (1995) focused their research on industry-level investment in the U.S. manufacturing sector. They investigated the effect of both the change in the real value of dollar and its volatility on the change in investment using annual data from 1972 to 1986. They also laid the groundwork for analyzing the theoretical micro-foundations for exchange rate effects on investment. Although the predictions of their theoretical model were highly dependent on the assumption of a log-normal distribution for the exchange rate, they did identify the theoretical underpinnings for the exchange rate to affect investment through two primary channels: the export channel, through which the exchange rate affects the competitiveness of U.S. goods in export markets; and the cost channel, through which the exchange rate affects the cost of imported intermediate goods.

Using benchmark input-output accounts to develop a measure of the share of imported inputs used in production and comparing it to the export share of revenues, Campa and Goldberg (1995) concluded that the external exposure of U.S. manufacturing industries changed over time and, on average, most industries became net importers. Again, they found that the effects of exchange rate volatility on investment were not robust in various specifications, and any significant effect was quantitatively very small. In regard to the change in the real value of the dollar, Campa and Goldberg (1995) generally found a negative net effect on investment when the exchange rate was interacted with export share and a positive net effect when interacted with the imported input share. As a result, they concluded that the effect of the exchange rate on investment could be overstated if one did not control for different types of industry external exposure.

Campa and Goldberg (1997) focused on the evolving external orientation of industries within the manufacturing sector for four countries: the U.S., the U.K., Canada and Japan. For the U.S., they concluded that manufacturing industries became increasingly integrated with the global economy over the period of 1972 to 1995. In regard to export orientation, Campa and Goldberg (1997) found that the share of export revenues roughly doubled for the entire manufacturing sector over this time period, yet the relative pattern of export orientation remained stable. In other words, the industries with relatively high export shares in the mid-1970s were still the most export oriented industries in the mid-1990s. In regard to import penetration, however, Campa and Goldberg (1997) found that while overall exposure to import competition increased from 1972 to 1995, the extent to which import penetration increased differed greatly across industries. Lastly, the authors found that U.S. manufacturing industries had steadily increased their use of imported inputs and attributed much of this increase to the sustained period of dollar appreciation in the first half of the 1980s.

Campa and Goldberg (1999) extended these earlier studies and formally developed what has become the standard theoretical model for the relationship between exchange rates and investment. They started with a standard adjustment cost model of investment and derived the microfoundations for the relationship between investment and the real exchange rate, including measures of external orientation. A complete derivation of this model will be given in next subsection.

2.1.2 Theoretical Model of Exchange Rates and Investment

This subsection presents the full derivation of the theoretical relationship between the exchange rate and investment under imperfectly competitive product markets as originally developed by Campa and Goldberg (1999). The basic framework is that of the standard adjustment cost model of investment extended to account for export sales and the use of imported inputs into production, both of which introduce exchange rate exposure to the producer. The general approach is that investment is an increasing function of the expected marginal profitability of capital and, by incorporating external exposure, the exchange rate affects the expected marginal profitability of capital.

The firm chooses investment to maximize the expected present value of the stream of future profits. Assume capital is quasi-fixed, which means that net increments to the capital stock are subject to adjustment costs. The adjustment costs are assumed to be increasing and convex (*i.e.* the adjustment costs increase at an increasing rate, which forces the firm to think seriously about the future before choosing the level of investment). Assume the only source of uncertainty about the future is the exchange rate. The timing associated with the firm's decision is subject to the following steps:

- Step 1: the firm observes the exchange rate at the beginning of period t.

- Step 2: the firm chooses its variable inputs and output level for period t and observes the profits for period t.

- Step 3: given current profits (t) and expected future profits ($t + 1 \to \infty$), the firm chooses the level of investment for period t.

- Step 4: new capital from investment becomes productive at the beginning of period $t + 1$ (*i.e.* assume a one-period time-to-build lag).

The maximized value of the firm at time t is represented by

$$V_t\left(K_t, e_t\right) = \max_{\{I_\tau\}_{\tau=t}^{\infty}} \mathrm{E}\left[\sum_{\tau=0}^{\infty} \beta^{\tau}\Big(\Pi\left(K_{t+\tau}, e_{t+\tau}\right) - c\left(I_{t+\tau}\right) - I_{t+\tau}\Big)\Big|\, \Omega_{\tau}\right] \tag{2.1}$$

subject to the capital accumulation constraint[1]

$$K_{t+1} = (1-\delta)\, K_t + I_t \tag{2.2}$$

where V_t is the expected present value of the stream of future profits, K_t is the beginning-of-period t capital stock, e_t is the period t exchange rate in terms of domestic currency per unit of foreign currency,[2] I_t is the level of investment in period t, β is the discount rate, Π is the profit function, c is the capital adjustment cost function, and δ is the depreciation rate. Since the exchange rate is assumed to be the only source of uncertainty, the expectation operator applies to e conditional on the time t information set Ω_t.

The first order condition for the maximization problem is[3]

$$\begin{aligned} \mathrm{E}\big[V_t^k|\Omega_t\big] &= 1 + \frac{\partial c\left(I_t\right)}{\partial I_t} \qquad \text{where} \\ V_t^k &= \sum_{\tau=1}^{\infty} \beta^{\tau}\left(1-\delta\right)^{\tau-1} \frac{\partial \Pi\left(K_{t+\tau}, e_{t+\tau}\right)}{\partial K_{t+\tau}} \end{aligned} \tag{2.3}$$

This equation states that the expected present value of the future stream of profits generated by an additional unit of capital (the sum of the discounted marginal profitabilities of capital) equals the marginal cost of an additional unit of capital (which in this model includes adjustment costs). For increasing and convex adjustment costs, assume that the cost of adjustment function is

$$c\left(I_t\right) = \frac{\gamma}{2}\left(I_t - \mu\right)^2 \tag{2.4}$$

---

[1] Due to the one-period time-to-build lag assumption, the capital accumulation constraint takes this forward looking form as opposed to the more traditional $K_t = I_t + (1-\delta)K_{t-1}$. The change does not affect the inherent assumption that the depreciation profile is based on a constant annual rate of capital consumption over the life of the asset (*i.e.* geometric depreciation).

[2] An increase in e indicates a domestic currency depreciation and a decrease in e indicates a domestic currency appreciation. Note: the exchange rate is only measured in this manner for the theoretical derivation. In all previous studies that are surveyed and all analyses presented in Chapters 4 and 5, the exchange rate is always included in the empirical specification as the real value of the dollar.

[3] Campa and Goldberg publish a τ exponent on $(1-\delta)$, which may be incorrect.

which is quadratic and homogeneous of degree one in investment, and where γ and μ are parameters. This model of adjustment costs is similar to that of Gilchrist and Himmelberg (1995); according to Chirinko (1993), a larger γ yields a slower response in investment. Using this adjustment cost function the first order condition becomes

$$I_t = \mu' + \frac{1}{\gamma}\,\mathrm{E}\big[V_t^k|\Omega_t\big] = \mu' + \sum_{\tau=1}^{\infty} \lambda^\tau\,\mathrm{E}\big[\Pi_{t+\tau}^k|\Omega_\tau\big] \tag{2.5}$$

where $\mu' = \mu - 1/\gamma$, $\lambda = \beta\,(1-\delta)\,[\gamma\,(1-\delta)]^{-1/\tau}$ and $\Pi_{t+\tau}^k$ is the marginal profitability of capital.[4] In order for the firm to maximize its value, then, current investment should be based upon the discounted sum of the expected marginal profitabilities of capital.

To determine the marginal profitability of capital, approach the profit maximization problem by noting that the firm observes the exchange rate, chooses its output in foreign and domestic markets and makes its choice of domestic and foreign variable inputs. The equation to maximize per-period profits gross of investment is, therefore,

$$\Pi\,(K_t, e_t) = \max_{q_t, q_t^*, L_t, L_t^*} p\,(q_t, e_t)\,q_t + e_t p^*\,(q_t^*, e_t)\,q_t^* - w_t L_t - e_t w_t^* L_t^* \tag{2.6}$$

subject to

$$q_t + q_t^* = f(K_t, L_t, L_t^*)$$

where q_t and q_t^* are the quantities supplied to the domestic and foreign markets, L_t and L_t^* are the domestic and foreign variable inputs, $p\,(\cdot)$ and $p^*\,(\cdot)$ are the domestic and foreign demand curves faced by the firm, w_t and w_t^* are the domestic and foreign unit variable costs, and $f(\cdot)$ is a constant returns to scale production function.[5] The exchange rate affects the demand for the firm's products through changes in the quantities supplied by its competitors or changes in the overall number of competitors. These shifts in demand imply that prices (or markups) are altered in response to exchange rate changes. Also, the profit maximization condition above clearly outlines the three channels by which exchange rates affect profits: home market revenues $p\,(q_t, e_t)\,q_t$, export market revenues $e_t p^*\,(q_t^*, e_t)\,q_t^*$, and imported input costs $e_t w_t^* L_t^*$. The exchange rate effects on home

[4] Campa and Goldberg publish that $\lambda = \beta\,(1-\delta)\,\gamma^{-1/\tau}$, which may be incorrect.

[5] Note that this framework assumes not only that capital is quasi-fixed, but also that it is domestically supplied, which is a reasonable assumption for the United States. In contrast, Harchaoui, Tarkhani and Yuen (2005) allow capital to be purchased from foreign markets in their study of the exchange rate effects on investment in Canadian manufacturing industries.

market revenues are intended to capture the possibility of import competition or the existence of wealth effects that potentially shift the demand schedule for products in the domestic market.

Using the Lagrangian multiplier Λ for profit maximization, the first order conditions are

$$\begin{aligned}
\frac{\partial \pi_t}{\partial q_t} &= p\left(q_t, e_t\right) + q_t \frac{\partial p\left(q_t, e_t\right)}{\partial q_t} - \Lambda = 0 \\
\frac{\partial \pi_t}{\partial q_t^*} &= e_t p^*\left(q_t^*, e_t\right) + e_t q_t^* \frac{\partial p^*\left(q_t^*, e_t\right)}{\partial q*_t} - \Lambda = 0 \\
\frac{\partial \pi_t}{\partial L_t} &= -w_t + \Lambda \frac{\partial f}{\partial L_t} = 0 \\
\frac{\partial \pi_t}{\partial L_t^*} &= -e_t w_t^* + \Lambda \frac{\partial f}{\partial L_t^*} = 0
\end{aligned}$$

Allowing the price elasticity of demand[6] for the domestic and foreign markets to be η_t and η_t^* the first order conditions yield the following relationships:

$$\begin{aligned}
\left(1 + \eta_t^{-1}\right) p\left(q_t, e_t\right) = \left(1 + \eta_t^{*-1}\right) e_t p^*\left(q_t^*, e_t\right) \\
w_t = \left(1 + \eta_t^{-1}\right) p\left(q_t, e_t\right) \frac{\partial f}{\partial L_t} \\
e_t w_t^* = \left(1 + \eta_t^{*-1}\right) p^*\left(q_t^*, e_t\right) \frac{\partial f}{\partial L_t}
\end{aligned} \tag{2.7}$$

To obtain a relationship for the marginal profitability of capital also differentiate by K_t

$$\Pi_t^k = \frac{\partial \pi_t}{\partial K_t} = \left(1 + \eta_t^{-1}\right) p\left(q_t, e_t\right) \frac{\partial f}{\partial K_t} \tag{2.8}$$

To disentangle the marginal product of capital, first divide the profit equation by K_t

$$\frac{\pi_t}{K_t} = \frac{p\left(q_t, e_t\right) q_t + e_t p^*\left(q_t^*, e_t\right) q_t^*}{K_t} - w_t \frac{L_t}{K_t} - e w_t^* \frac{L_t^*}{K_t}$$

For ease of notation, let $p_t = p(q_t, e_t)$ and $p_t^* = p^*(q_t^*, e_t)$, and substitute for w_t and $e_t w_t^*$ from the profit maximization first order conditions (Equation (2.7)) to obtain

$$\frac{\pi_t}{K_t} = \frac{p_t q_t + e_t p_t^* q_t^*}{K_t} - \left(1 + \eta_t^{-1}\right) p_t \left[\frac{L_t}{K_t} \frac{\partial f}{\partial L_t} + \frac{L_t^*}{K_t} \frac{\partial f}{\partial L_t^*}\right] \tag{2.9}$$

[6] The price elasticity of demand is $\frac{p}{q} \frac{\partial q}{\partial p}$.

Since the production function is constant returns to scale, it is homogenous of degree one; therefore, Euler's Theorem implies

$$\frac{\partial f}{\partial K_t}K_t + \frac{\partial f}{\partial L_t}L_t + \frac{\partial f}{\partial L_t^*}L_t^* = q_t + q_t^*$$

Rearranging yields

$$\left[\frac{L_t}{K_t}\frac{\partial f}{\partial L_t} + \frac{L_t^*}{K_t}\frac{\partial f}{\partial L_t^*}\right] = \frac{q_t + q_t^*}{K_t} - \frac{\partial f}{\partial K_t} \tag{2.10}$$

Substitute Equation (2.10) into Equation (2.9) to obtain

$$\frac{\pi_t}{K_t} = \frac{p_t q_t + e_t p_t^* q_t^*}{K_t} - \left(1 + \eta_t^{-1}\right) p_t \left[\frac{q_t + q_t^*}{K_t} - \frac{\partial f}{\partial K_t}\right] \tag{2.11}$$

Solving for the marginal product of capital in Equation (2.11) and substituting it into Equation (2.8) yields the following expression for the marginal profitability of capital:

$$\Pi_t^k = \frac{\pi_t}{K_t} - \frac{p_t q_t + e_t p_t^* q_t^*}{K_t} + p_t\left(1 + \eta_t^{-1}\right)\frac{q_t + q_t^*}{K_t} \tag{2.12}$$

The marginal profitibility of capital in Equation (2.12) can also be expressed in terms of price-over-cost markups. Define the markups as

$$\begin{aligned} \kappa_t &= \frac{p_t}{MC_t} = \frac{1}{1 + \eta_t^{-1}} \\ \kappa_t^* &= \frac{e_t p_t^*}{MC_t} = \frac{1}{1 + \eta_t^{*-1}} \end{aligned} \tag{2.13}$$

where κ_t and κ_t^* are the markups in the domestic and foreign markets and MC_t is marginal cost. By using the markups in Equation (2.13) the marginal profitability of capital can be expressed as

$$\Pi_t^k = \frac{1}{K_t}\left[\kappa_t^{-1} p_t q_t + \kappa_t^{*-1} e_t p_t^* q_t^* - \left(w_t L_t + e_t w_t^* L_t^*\right)\right] \tag{2.14}$$

Assuming that exchange rate changes are permanent and uncorrelated over time and that the only source of uncertainty is the exchange rate, the information set Ω_t in Equation (2.5) contains only the past and current marginal profitabilities of capital. As a result, the expected marginal profitability of capital in all future periods is equal to the current marginal profitability of capital, or $\mathrm{E}\left[\Pi_{t+\tau}^k|\Omega_\tau\right] = \Pi_t^k$.

Therefore, Equation (2.5) becomes

$$I_t = \mu' + \Pi_t^k \sum_{\tau=1}^{\infty} \lambda^\tau \tag{2.15}$$

In order to simplify Equation (2.15), recall that

$$\lambda = \frac{\beta\,(1-\delta)^{\frac{\tau-1}{\tau}}}{\gamma^{\frac{1}{\tau}}}$$

Therefore,

$$I_t = \mu' + \frac{\Pi_t^k}{\gamma\,(1-\delta)} \sum_{\tau=1}^{\infty} \left[\beta\,(1-\delta)\right]^\tau \tag{2.16}$$

where $|\beta| < 1$ and $|(1-\delta)| < 1$, so $|\beta\,(1-\delta)| < 1$; therefore, the summation in Equation (2.16) can be expressed as an infinite geometric series[7] and reduces to

$$I_t = \mu' + A\Pi_t^k \tag{2.17}$$

where $A = \beta/\gamma\,[1-\beta\,(1-\delta)]$.[8] Finally, the optimal investment to maximize the value of the firm becomes

$$I_t = \mu' + \frac{A}{K_t}\left[\kappa_t^{-1} p_t q_t + \kappa_t^{*-1} e_t p_t^* q_t^* - \left(w_t L_t + e_t w_t^* L_t^*\right)\right] \tag{2.18}$$

Lastly, to determine the effect of the exchange rate on investment, differentiate Equation (2.18) with respect to e_t. In order to show clearly how Campa and Goldberg obtain their final result, I differentiate each term separately. The first term is $\kappa_t^{-1} p_t q_t$:

$$\begin{aligned}
\frac{\partial \kappa_t^{-1} p_t q_t}{\partial e_t} &= \frac{p_t q_t}{\kappa_t}\left(\frac{1}{p_t}\frac{\partial p_t}{\partial e_t} - \frac{1}{\kappa_t}\frac{\partial \kappa_t}{\partial e_t}\right) \\
&= \frac{p_t q_t}{\kappa_t}\left(\frac{e_t}{p_t}\frac{\partial p_t}{\partial e_t} - \frac{e_t}{\kappa_t}\frac{\partial \kappa_t}{\partial e_t}\right)\frac{1}{e_t} \\
&= \frac{p_t q_t}{\kappa_t}\left(\eta_{p,e} - \eta_{\kappa,e}\right)\frac{1}{e_t} \\
&= \frac{TR_t}{\kappa_t}\frac{p_t q_t}{TR_t}\left(\eta_{p,e} - \eta_{\kappa,e}\right)\frac{1}{e_t} \\
&= \frac{TR_t}{\kappa_t}\left(1-\chi_t\right)\left(\eta_{p,e} - \eta_{\kappa,e}\right)\frac{1}{e_t}
\end{aligned}$$

---

[7]An infinite geometric series of the form $\sum_{k=m}^{\infty} ar^k = \frac{ar^m}{1-r}$ for $|r| < 1$.

[8]According to what Campa and Goldberg publish for λ, $A = \beta\,(1-\delta)\,/\gamma\,[1-\beta\,(1-\delta)]$; however, they publish the same value for A as noted here.

where $\eta_{p,e}$ is the domestic market exchange rate pass-through elasticity, $\eta_{\kappa,e}$ is the domestic markup elasticity with respect to the exchange rate, TR_t is total revenue, and χ_t is the share of total revenue associated with foreign sales. The second term is $\kappa_t^{*-1} e_t p_t^* q_t^*$, which is differentiated in a similar fashion to the first term to yield

$$\frac{\partial \kappa_t^{*-1} e_t p_t^* q_t^*}{\partial e_t} = \frac{TR_t}{\kappa_t^*} \left(\chi_t\right) \left(1 + \eta_{p^*,e} - \eta_{\kappa^*,e}\right) \frac{1}{e_t}$$

where $\eta_{p^*,e}$ is the foreign market exchange rate pass-through elasticity and $\eta_{\kappa^*,e}$ is the foreign markup elasticity with respect to the exchange rate. The next term is $w_t L_t$. Campa and Goldberg assume that domestically supplied input costs are insensitive to exchange rate movements; therefore,

$$\frac{\partial w_t L_t}{\partial e_t} = 0$$

The final term is $e_t w_t^* L_t^*$:

$$\begin{aligned} \frac{\partial e_t w_t^* L_t^*}{\partial e_t} &= e_t L_t^* \frac{\partial w_t^*}{\partial e_t} + w_t^* L_t^* \\ &= w_t^* L_t^* \left(1 + \frac{e_t}{w*_t} \frac{\partial w_t^*}{\partial e_t}\right) \\ &= TR_t \left(\frac{e_t w_t^* L_t^*}{TR_t}\right) \left(1 + \eta_{w^*,e}\right) \frac{1}{e_t} \end{aligned} \tag{2.19}$$

where $\eta_{w^*,e}$ is the imported input elasticity with respect to exchange rate movements.[9] Equation (2.19) can be expressed in terms of the markup with a few tricks. Because the production function exhibits constant returns to scale, marginal cost equals average variable cost; therefore

$$TR_t = \left(p_t q_t + p_t^* q_t^*\right) \frac{AVC_t}{MC_t} = \left(\kappa_t q_t + \kappa_t^* q_t^*\right) AVC_t \tag{2.20}$$

where AVC_t is average variable cost. Campa and Goldberg note that markups cannot be distinguished between domestic and foreign markets in their data set, so they let $\kappa_t = \kappa_t^* = \tilde{\kappa_t}$ where $\tilde{\kappa_t}$ is the average markup. As a result, Equation (2.20) reduces to

$$TR_t = \tilde{\kappa_t} \left(q_t + q_t^*\right) AVC_t \tag{2.21}$$

[9]Campa and Goldberg publish that the imported input elasticity is equal to $\left(1 + \eta_{w^*,e}\right)$, which may be incorrect.

Letting g_t equal total production costs, Equation (2.21) reduces to

$$TR_t = \tilde{\kappa_t} g_t \tag{2.22}$$

Substitute Equation (2.22) into Equation (2.19) to obtain

$$\begin{aligned} \frac{\partial e_t w_t^* L_t^*}{\partial e_t} &= TR_t \left(\frac{e_t w_t^* L_t^*}{\tilde{\kappa_t} g_t} \right) (1 + \eta_{w^*,e}) \frac{1}{e_t} \\ &= \frac{TR_t}{\tilde{\kappa_t}} (1 + \eta_{w^*,e}) \alpha_t \frac{1}{e_t} \end{aligned} \tag{2.23}$$

where α_t is the share of imported inputs in total production costs.[10] Keeping the assumption that the domestic and foreign markups are equal to the average markup and combining the individual terms noted above, we obtain the following result for the partial derivative of investment with respect to the exchange rate:

$$\begin{aligned} \frac{\partial I_t}{\partial e_t} = \frac{A_t'}{\tilde{\kappa_t}} \Big[&(\eta_{p,e} - \eta_{\kappa,e}) (1 - \chi_t) \\ &+ (1 + \eta_{p^*,e} - \eta_{\kappa^*,e}) \chi_t - (1 + \eta_{w^*,e}) \alpha_t \Big] \frac{1}{e_t} \end{aligned} \tag{2.24}$$

where $A_t' = (A/K_t) \, TR_t$.

The three terms inside the brackets in Equation (2.24) provide a concise set of insights into the various channels for the exchange rate to affect investment. First of all, both the share of exports in total revenues and the share of imported inputs in total production costs have a direct effect on the investment response to exchange rate changes.[11] The share of exports has a positive effect on investment, so a depreciation in the domestic currency will increase the level of investment via this channel. The share of imported inputs has a negative effect, so a home currency depreciation will decrease the level of investment through this channel. The exchange rate also affects investment indirectly through the pricing and markup behaviors in three distinct markets: the domestic market for final goods, the foreign market for final goods and the domestic market for imported inputs.

The first term inside the brackets, $(\eta_{p,e} - \eta_{\kappa,e})(1 - \chi_t)$, will be referred to as the domestic channel. This channel measures how the exchange rate indirectly affects investment through the

---

[10] Note that $\alpha_t = \frac{e_t w_t^* L_t^*}{g_t}$. Recall that w_t^* and L_t^* are the unit cost and quantity (respectively) of foreign variable inputs, and (although the notation may be somewhat confusing) do not include foreign labor inputs, as all labor inputs are assumed to be domestic

[11] Note that χ_t and α_t are multiplied by 1 in the second and third terms, respectively.

share of sales in the home market. The final weight that these sales carry on the investment response depends upon the exchange rate elasticities of domestic prices and markups, which in turn, depend upon the competitive structure of the home market. For example, if foreign competitors squeeze their markups instead of passing through a domestic currency depreciation into their home market prices (price elasticity relatively smaller than markup elasticity), then the share of domestic sales will have a lower weight on the firm's investment response.

In other words, prices at home may not change as much when the domestic currency depreciates, because foreign competitors reduce their markups in order to maintain market share. Because prices and market share remain relatively stable in such a case, profitibility and investment will remain relatively unchanged due to movements in the exchange rate. The degree to which these prices and markups vary is dependent upon the competitive structure of the domestic market. In a market with relatively little import competition, firms with higher pricing power would be able to pass through exchange rate changes into their prices without adjusting their markups to a significant degree. Firms with less pricing power, however, would adjust their markups to pass through less of the exchange rate changes into their prices.

In a similar fashion, the pricing and markup behaviors in the foreign market for final goods are affected by changes in the exchange rate and indirectly impact the weight that the export share has on changes in investment. This result can clearly be seen in the second term inside the brackets, $(1 + \eta_{p^*,e} - \eta_{\kappa^*,e})\, \chi_t$, which will be referred to as the export channel. In this channel, the direct effect of the export share on the investment response to exchange rate changes can be either amplified or dampened depending upon the difference in the exchange rate elasticities of foreign prices and markups. The sum of the domestic channel and the export channel can be considered the revenue channel, because it takes into consideration the effect of the exchange rate on investment due to the combination of domestic and foreign sales revenue for the firm.

The third term inside the brackets, $(1 + \eta_{w^*,e})\, \alpha_t$, will be referred to as the cost channel. This channel measures the effect of the exchage rate on investment through the share of imported inputs used in production. Once again, the total effect of the cost channel depends upon an indirect effect in the form of the exchange rate elasticity of foreign unit variable costs. If these costs are highly elastic with respect to the exchange rate, then the share of imported inputs used in production will have a greater impact upon the investment response to changes in the exchange rate.

Finally, note that the terms inside the brackets of Equation (2.24) are scaled by the term

$$\frac{A_t'}{\tilde{\kappa_t}} = \left(\frac{TR_t}{K_t}\right)\left(\frac{\beta}{\gamma\left[1-\beta\left(1-\delta\right)\right]}\right) \tag{2.25}$$

The investment response to the exchange rate, therefore, will be smaller for firms with high costs of capital adjustment (γ) or high rates of depreciation (δ) and larger for firms with a higher discount rate (β) or low ratio of capital to revenues (K_t/TR_t).

Overall, the theoretical model of Campa and Goldberg (1999) provides a concise set of predictions for the different channels through which the exchange rate could affect the marginal profitability and, hence, the investment decisions of a representative firm. The model identifies two channels through which the exchange rate could have a *direct* effect upon the marginal profitability of the firm. The export channel recognizes the effect of exchange rate changes upon the competitiveness of domestic goods in export markets, while the cost channel recognizes the effect upon the cost of imported inputs used in production. These channels are represented in the two main measures of external orientation that Campa and Goldberg (1999) interacted with the real exchange rate: the share of exports in total revenue and the share of imported inputs in total costs. The model also identifies how the exchange rate could *indirectly* affect investment. The indirect effects work through the pricing and markup decisions of firms; as a result, the direct effects of the exchange rate could be dampened or amplified depending on the magnitude of the exchange rate markup and pass-through elasticities.

2.1.3 Empirical Applications of the Campa-Goldberg Model

Campa and Goldberg (1999) applied their model to investigate the effect of the real exchange rate on investment in manufacturing industries in the U.S., the U.K., Canada, and Japan. Using panel data from 1972 to 1993 for U.S. manufacturing industries, the authors interacted their measures of external orientation with the real value of the dollar while controlling for accelerator effects, the cost of other inputs, and the cost of capital. For U.S. investment, the export channel effect was found to be negative and statistically significant for all industries and across different sub-samples defined by high or low markup rates. The cost channel effect, however, was found to be positive and statistically significant only in the low markup industries. Although Campa and Goldberg (1999) made this finding of a positive effect of the value of the dollar on investment a cornerstone to their conclusions, the significant results that they did find were not robust across different samples within or across countries.

A few authors have extended the industry level framework of Campa and Goldberg (1999) to other countries and with similar results. Harchaoui et al. (2005) modified the analysis for Canada by including the possibility of imported capital goods in their investment equation. Their results suggested that appreciations tended to have an overall negative effect on investment when the volatility of the Candian dollar was low. Although the authors did not use measures of external exposure in the analysis, their results suggested that the export channel dominated within the investment to exchange rate linkage for Canadian manufacturing when the exchange rate changes were perceived to be permanent. Swift (2005, 2007) used quarterly data for the Australian manufacturing sector to estimate industry-specific coefficients for the exchange rate effect on investment by interacting the exchange rate with measures of external orientation. For the Australian manufacturing sector as a whole, Swift found that the real exchange rate was significant and had the expected signs *via* both the export channel and the cost channel (negative for the export channel and positive for the cost channel). Caglayan and Munoz-Torres (2008) analyzed Mexico's manufacturing industries; they found that only the export channel was signficant for industry level investment (*i.e.* a negative net effect).

Others extended the framework of Campa and Goldberg (1999) to investigate the relationship between investment and the exchange rate at the firm level. Nucci and Pozzolo (2001) used data on over 1,000 Italian manufacturing firms to perform their analysis. They used similar measures of external exposure as those of Campa and Goldberg (1999), but the imported input share was modified to include both industry- and firm-specific information. They also added an investigation of the role of import competition and the effect of the exchange rate on investment through its effect on domestic revenues. By using firm level data, they were also able to control for firm-specific effects. Nucci and Pozzolo (2001) concluded that these individual idiocyncranies, although unobserved, reflected important characteristics of a firm that may have been masked by more aggregated analyses. They also found evidence that the real exchange rate had a negative effect on investment via the export channel and a positive effect via the cost channel in their sample of Italian manufacturing firms. Prapassornmanu (2009) conducted a similar analysis for Thai manufacturing firms and found similar, though less robust, results.

Leonida et al. (2006) conducted an empirical analysis of the effects of the exchange rate on investment for a large sample of U.K. firms from 1992-2000. They estimated firm-level export and import exposure and found a negative effect of the exchange rate on investment through its effect on revenues and a positive effect through its effect on the cost of imported intermediate goods. They also extended the literature on exchange rates and investment by incorporating interactions between the changes in the real exchange rate and proxies for financially constrained investment. Overall, Leonida et al. (2006) found that financially constrained firms had investment that was more sensitive to changes in the exchange rate than firms with stronger financial positions.

2.1.4 Aggregate and Cross-country Studies

Blecker (2007) re-opened the question of the effect of the exchange rate on investment in U.S. manufacturing with a time series analysis using aggregate data. He extended the period of investigation to 2004 and analyzed the role that the exchange rate may have had on investment using an autoregressive distributed lag model. Blecker attempted to align the literature on exchnage rates and investment with the portion of the investment function literature that relies on distributed lag models to investigate financially constrained investment. He found evidence of a large, negative net effect of the level of the real value of the dollar on investment, and his results were robust to several different specifications that controlled for the real interest rate or the user cost of capital, accelerator effects, and cash flow or profits representing liquidity constraints. Blecker concluded that the real exchange rate affected U.S. manufacturing investment primarily through the channel of financial or liquidity constraints. Overall, his estimates for the negative effect of the exchange rate were much larger than those found in the previous industry level studies of the U.S. One drawback to his research, however, was the inclusion of the autoregressive investment term, which limited the overall lag structure of the control variables, and may have led to an overstatement of the long-run exchange rate effect.

Other recent work on the linkages between the exchange rate and investment involved the use of error-corrrection models across many countries. Landon and Smith (2007) examined the short-run and long-run effects of exchange rate changes on investment in OECD countries. They pooled sector level data across countries, added sectors other than manufacturing, and included the real wage as a control variable. They found that a currency appreciation led to an increase in investment in the short run (*i.e.* a net positive effect of the exchange rate through the cost channel), while there was no significant effect of the exchange rate on investment in the long run. Bahmani-Oskooee and Hajilee (2010) performed a similar analysis at the aggregate level of investment across fifty countries, and they also found that short-run effects tended to be more important than long-run effects in the exchange rate and investment relationship. For the U.S., Bahmani-Oskooee and Hajilee (2010) found evidence of a net positive effect of real dollar appreciation in the short run and an insignificant effect in the long run.

2.1.5 Critical Review

To my knowledge, the survey presented above covers the total body of work in the research on linkages between exchange rates and domestic investment. Given this body of work, it is clear that the model of Campa and Goldberg (1999) has become the standard theoretical framework used to investigate the effect of the exchange rate on investment in the disaggregated studies at the industry or firm level. Nevertheless, I wish to identify some potential shortcomings that arise from translating this framework into empirical analysis.

First, a majority of the previous studies at the industry and firm level rely on interacting the exchange rate with measures of international exposure. Often, these exchange rate terms are interacted further with measures of the markup. Including these interaction terms in the empirical specification flows directly from the theoretical predictions regarding the channels of transmission for the exchange rate to affect investment as identified in Equation (2.24). Estimating coefficients for the interaction terms does provide insight as to whether a domestic currency appreciation affects investment in the direction that we expect (negatively through the export channel and positively through the cost channel), and many studies have investigated this with mixed results. From a practical standpoint, however, interpreting the exchange rate effect from these coefficients or comparing results across different studies becomes difficult, because one cannot easily disentangle the individual effects of each variable within the interacted terms.

The exchange rate interaction terms in most of the previous studies utilize the export share and the imported input share as the measures of external exposure. In moving from the theoretical channels of transmission in Equation (2.24) to an empirical specification, most previous studies estimated a portion of the domestic channel effect in the coefficient on the export share interacted exchange rate term. Although an appreciation of the real value of the domestic currency is expected to have a negative effect on investment via both the domestic and export channels, one cannot clearly delineate the two channels, which makes it difficult to identify the effect of exchange rate on investment due to the competitiveness of imported final goods. Another practical concern that has been ignored in previous studies is that including multiple exchange rate interaction terms likely introduces a high degree of multicollinearity within the empirical model.

Taken together, these issues provide a motivation for eliminating the exchange rate interaction terms altogether and replacing them with a single measure of the industry-specific exchange rate as developed in Goldberg (2004). Using a similar method to the construction of the broad, trade-weighted real value of the U.S. dollar by the Federal Reserve, she developed a similar exchange rate index that takes into consideration only the volume of trade that occurs within large industrial classifications for the U.S. economy. In addition, Goldberg (2004) created exchange rate indexes that were weighted only by exposure to export markets or to penetration by imported goods. Overall, she concluded that aggregate exchange rate indexes could be less effective than industry-specific indexes in capturing the changes in industry competitive conditions induced by moves in specific bilateral exchange rates. To my knowledge, however, no one has used these trade-weighted exchange rate indexes in a study of investment prior to the present research.

In addition, there are two related assumptions in the derivation of the theoretical model of Campa and Goldberg (1999) that have affected the empirical specification of previous studies and deserve additional attention. The first assumption is that exchange rate changes are permanent and uncorrelated over time, which combined with the assumption that the exchange rate is the only source of uncertainty implies that the firm equates its expected marginal profitability of capital in all future periods to its the current marginal profitability. In other words, all of the necessary information for a firm to choose its desired capital stock lies in the current period's exchange rate.

Although not addressed explicitly in the Campa and Goldberg framework, the assumption of permanent exchange rate changes is also related to the descriptive theory of Worthington (1991). She predicted that if an exchange rate shock is expected to be transitory, firms may choose to alter more easily changed inputs, such as labor. On the other hand, an exchange rate shock that is expected to be permanent may induce firms to change more costly inputs, such as capital. Taken together, the assumption of permanent exchange rate changes seems to be critical to the exchange rate having an effect on the desired capital stock of a firm. What this ignores, however, is that due to the competitive environment or asymmetric information, a firm may alter the rate of investment in order to meet its desired capital stock.

The second assumption is the one-period time-to-build assumption for capital investment. Combined with exchange rate changes that are perceived to be permanent, these assumptions make the choice and obtainment of the desired capital stock a short-run oriented phenomenon. Actual investment expenditures, however, tend to lag behind planned investment decisions and increases or decreases in the desired capital stock typically manifest themselves in a planned investment structure with suitable lags. The main implication of these two assumptions on the previous studies that use the Campa and Goldberg framework is that the exchange rate and all other variables are included in the empirical specification with only a single lag. Interestingly, Campa and Goldberg (1999) is the only study that included a permanent component of the exchange rate in the empirical analysis, which suggests that other authors either ignored the assumption of permanent exchange rate changes or found it unimportant for empirical work. The question remains, however, as to whether these two assumptions are overly restrictive when translating the theoretical framework into an empirical specification.

Last, a majority of the previous studies based upon the Campa and Goldberg framework ignored the possibility of, and did not control for, financial or liquidity constraints on investment. These studies assumed that firms are not financially constrained in reaching their desired capital stocks, an assumption that has been challenged both theoretically and empirically, as will be discussed in the next section. Also, Campa and Goldberg only included a measure of interest rates, but did not control for a broader measure of the cost of capital as is standard in most of the general literature on investment functions. These are two important motivations for using an alternative estimation approach that is based on the more general investment function literature.

In general, the issues noted above highlight the gap between the literature on exchange rates and investment and the broader literature on investment functions. Following Campa and Goldberg (1999), the extent of the overlap in many of the previous studies is to append an interest rate and accelerator term as control variables in the empirical specification. Leonida et al. (2006) and Blecker (2007) are the two previous studies that tried to bridge the gap between the two strands of literature. While Leonida et al. (2006) adds measures of financial constraints to the Campa and Goldberg framework, Blecker (2007) adds the exchange rate to a commonly used empirical specification for the investment function. Given these different approaches, it is appropriate to highlight certain portions of the more general investment function literature that will be used to construct an alternative estimation approach in this study.

2.2 General Literature on the Investment Function

In this section, I provide a brief overview of the investment function literature that covers the role of accelerator effects, the user cost of capital, and financial or liquidity constraints. The literature on the investment function is voluminous, so I will focus on the most important theories and findings that will be applied in this study.

2.2.1 Accelerator and User Cost Models

The principle of acceleration in studies of investment and the business cycle has its origin in the works of Samuelson (1939a,b, 1959), Harrod (1936), and Hansen (1938). According to the accelerator principle, induced investment is proportional to changes in consumption, which given a marginal propensity to consume implies that investment is proportional to changes in national income (output). The interplay between the accelerator principle and the Keynesian multiplier would then yield fluctuations in economic activity. The ground-breaking work by Samuelson was a key component within the early, large macroeconomic models of the business cycle.

The neoclassical investment model, initially proposed in Jorgenson (1963) and Hall and Jorgenson (1967), switched the emphasis from a quantity-based explanation of investment to one that is also based on relative price, where the cost of purchasing or using capital (the user cost of capital) is most important. Starting with the optimization problem of a representative firm with a constant returns to scale Cobb-Douglas production function, profit maximization yields the following relationship for the desired level of the capital stock:

$$K^* = \alpha \frac{y}{c} \tag{2.26}$$

where K^* is the optimal level of capital, α is the elasticity of output with respect to capital, y is output, and c is the real user cost of capital. The relationship between changes in the desired capital stock and actual investment expenditures, however, is not instantaneous. Instead, a proportion of the investment expenditure necessary to meet the desired capital stock takes place over time. In addition, replacement investment must take place in order to account for the depreciation of capital. As a result, the flow of investment spending takes the form of a distributed lag function:

$$I_t = \sum_{s=0}^{\infty} \mu_s \Delta K^*_{t-s} + \delta K_t \tag{2.27}$$

where I_t is gross investment in period t, μ_s is the proportion of the change in the desired capital stock from period $t - s$ that results in investment expenditures in period t, and δ is the rate of depreciation. Given this formulation, investment is a weighted average of past changes in desired capital and replacement investment. This Jorgensonian model of investment is also referred to as the "flexible accelerator" model of investment, because the traditional accelerator model is included as the special case in which relative prices are constant.

In their empirical work on the effect of tax policy on investment behavior, Hall and Jorgenson (1967) included a combined measure of output and the user cost to approximate the desired capital stock, as indicated in Equation (2.26). Eisner and Nadiri (1968), Eisner (1969, 1970), and later Chirinko and Eisner (1983), however, found fault in using a combined measure of output and the user cost in models of investment. They showed that the assumption of a Cobb-Douglas production function was necessary for the theoretical relationship of the desired capital stock in Equation (2.26). They argued that this relationship was unnecessarily restrictive because it required that the elasticities of the desired capital stock with respect to both output and the user cost are unity (in absolute value), as shown below:

$$\eta_{K^*,y} = \left|\frac{\partial K^*}{\partial y}\right| = 1 = \left|\frac{\partial K^*}{\partial c}\right| = \eta_{K^*,c} \tag{2.28}$$

where $\eta_{K^*,y}$ is the elasticity of the desired capital stock with respect to output, and $\eta_{K^*,c}$ is the elasticity of the desired capital stock with respect to the user cost.

By separating the two components of the desired capital stock in their empirical work, Eisner and Nadiri (1968) found that the accelerator (or quantity) effect was actually more important for explaining investment behavior than the user cost (or relative price) effect, and they concluded that there should be no *a priori* assumption that the elasticites are both unity. Given this finding, Eisner and Nadiri (1968) and Eisner (1969, 1970) suggested that a preferable assumption is a constant elasticity of substitution (CES) production function, which yields the following relationship for the desired capital stock:

$$K_t^* = \zeta y_t c_t^{-\sigma} \tag{2.29}$$

where K^* is the optimal level of capital, ζ is the CES distribution parameter, y is output, c is the real user cost of capital, and σ is the user cost elasticity. Using this type of framework allows one to estimate the elasticity of both the accelerator and the user cost separately, and more importantly with differing lag structures (as in Bischoff et al. (1971)).

Chirinko (1993) critically surveyed the modeling strategies and empirical results in the large body of work on the investment function up to that point. He noted that with the development of the neoclassical investment model, many researchers relied increasingly on formal models to investigate the impact of prices, quantities, and shocks on the investment spending by firms to achieve their desired capital stocks. Much of this research investigated the relative importance of price variables (interest rates or the user cost of capital) versus quantity variables (accelerator effects) that relied on capacity utilization or output growth rates. In regard to empirical evidence, Chirinko (1993) found that the most robust results were associated with the accelerator, while the results for the user cost were either tenuous or highly sensitive to model specification.

Both Chirinko (1993) and Cummins et al. (1994) noted that the failure of the neoclassical model to adequately explain business fixed investment led to the increased usage of q models, in which the q ratio is defined as the ratio of the market value of a firm's capital stock to its replacement cost. The idea that the q ratio could explain investment spending had its origin in the work of Keynes (1936) and earlier (but less appreciated) Veblen (1917). It was revitalized by Brainard and Tobin (1968) and Tobin (1969, 1978), who argued that investment spending is positively related to average q:

$$q_t^A = \frac{V_t}{p_t^I K_t} \tag{2.30}$$

where q_t^A is average q, V_t is the market value of the firm, and $p_t^I K_t$ is the replacement cost of the firm's existing capital stock. The general idea is that the market value of the firm should reflect expectations about the firm's return to capital, and hence the firm should increase its capital stock if the replacement cost of its existing stock is less than what is reflected by its market value. Overall, however, Chirinko (1993) and Cummins et al. (1994) found that that neoclassical models of the user cost of capital and q models both failed to explain investment as well as *ad hoc* models that emphasized sales or profit variables. In response, Chirinko (1993) recommended that using an incomplete theoretical model for empirical investigation may provide more valuable insight into investment behavior than a fully formed model that imposes too many restrictions on the analysis.

2.2.2 Models of Financial (or Liquidity) Constraints

One strand of the investment function literature that has relied heavily on *ad hoc* models is the part that has investigated the effect of financial structure and/or liquidity constraints on investment spending as suggested in Kalecki (1937), Steindl (1952), Minsky (1977, 1984, 1986), and Stiglitz and Weiss (1981). Neoclassical models of the user cost and q models of investment assumed that the supply of external funds was infinitely elastic to firms so that they could always obtain enough finance for the investment required to reach their desired capital stock over some period of time. Kalecki's principle of increasing risk suggested that marginal risk increased with the amount invested, which given a set amount of internal funds could limit the funds that could be raised externally in financial markets, thereby forcing the firm to rely more heavily on internal finance. Minsky's financial instability hypothesis suggested that cash flow requirements to service debt overhang (both interest payments and principal from previous changes to the desired capital stock) may restrict actual investment spending, especially if the firm is forced to rollover debt in a rising interest rate environment. Stiglitz and Weiss suggested that the underlying problem was that borrowers (firms) and lenders (financial investors in bond or equity markets) do not have the same information about the true prospects for investment projects or the firm's true ability to repay. In the absence of such full information, lenders would use cash flow as an observable indicator of the firm's ability to repay. Unlike output and the user cost, which affect the desired capital stock, these models predicted that cash flow would affect the flow of investment spending, *i.e.*, the rate at which the firm could achieve any given desired capital stock.

Overall, these studies suggested that a firm may face a wedge between the opportunity cost of internal funds and the cost of external financing. As a result, a financially constrained firm with lower cash flow may therefore be less likely to invest. Fazzari et al. (1988) pioneered the use of cash flow as an empirical indicator of financial frictions to investment. Instead of starting with a fully developed theoretical model, Fazzari et al. (1988) started with a reduced form of the investment equation:

$$(I/K)_{i,t} = f\,(X/K)_{i,t} + g\,(CF/K)_{i,t} + u_{i,t} \tag{2.31}$$

where $I_{i,t}$ is investment for firm i in period t, X is a vector of variables (possibly lagged) that have been emphasized as determinants of investment from a variety of theoretical perspectives, and $u_{i,t}$ is an error term. The function g is dependent on the firm's cash flow, $CF_{i,t}$ (also possibly lagged), and represents the sensitivity of investment to changes in the availability of internal finance.

Fazzari et al. (1988) tested various combinations of Tobin's q, sales, and/or the user cost of capital within the vector X, and they found that in a wide variety of models investment-cash flow sensitivities were a useful measure of the potential severity of financing constraints on the firm's investment decisions. Using retention ratios, they classified firms *a priori* into three levels of financial friction. A lower retention ratio suggested a tighter financial constraint for the firm. Their empirical results suggested that as financial constraints increased, investment became more sensitive to the operating cash flow of the firm.

The literature on financially constrained investment that followed from Fazzari et al. (1988) is large (for a brief survey, see Hubbard (1998)), but there also has been a debate over the usefulness of investment-cash flow sensitivities as measures of financial constraints. The debate began with the work of Kaplan and Zingales (1997) and Cleary (1999), and it continued in Fazzari et al. (2000), Kaplan and Zingales (2000) and Cleary et al. (2007). Kaplan and Zingales claimed that there was no basis to the fundamental assumption that investment-cash flow sensitivities increase monotonically with the degree of financing constraints. Using the subset of the most financially constrained firms identified in Fazzari et al. (1988), Kaplan and Zingales developed an entirely different ranking system for the level of financial friction facing firms that was based upon measures of financial health. In doing so, the authors found the exact opposite effect: firms that were least likely to be financial constrained had greater investment-cash flow sensitivities.

The response of Fazzari et al. (2000) was that the subset of 49 firms identified by Kaplan and Zingales (1997) was a poor choice for evaluation. Their argument was that this subset of firms was very small and relatively homogenous, so it did not truly reflect the extent of capital market imperfections experienced by most firms. On the other hand, Cleary (1999) found similar evidence as Kaplan and Zingales for a much larger sample of firms and a less subjective classification scheme. The main conclusion of both Kaplan and Zingales and Cleary was that investment-cash flow sensitivities were not good indicators for the effect of financial constraints in models of investment. In contrast, Chirinko and Schaller (1995) found evidence in favor of cash flow being more significant in Canadian firms where information problems were more severe. In general, one should consider the debate over the usefulness of cash flow as an indicator of financial or liquidity constraints as unsettled in the investment function literature. In regard to the empirical analysis of this study, I do not seek to add to the debate over the usefulness of cash flow senstivities but rather to control for their potential effect in a manner that is comparable to existing research.

2.2.3 Synthesis and Extensions

Chirinko et al. (1999) provided a synthesis of the earlier works on the accelerator and the neoclassical model with the studies on financial/liquidity constraints. In their distributed lag model of the level of investment, they included variables for sales and the user cost as determinants of the desired capital stock and also included a cash flow variable to control for the potential effect of financial constraints on investment. In addition, Chirinko et al. (1999) highlighted the difference between including an explanatory variable in levels or growth form. Because investment can be interpreted as related to the change in the desired capital stock, variables that are expected to affect the desired capital stock should be included in the empirical analysis in growth rate (or difference) form. Changes in the user cost of capital and the growth rate of sales/output are expected to affect the desired capital stock, so they were included in this form. On the other hand, given the firm's desired capital stock, a lower level of internal funds (cash flow or cash) may prevent the firm from investing as much as it wants to in order to reach that desired capital stock. To identify the channel of financial constraints, therefore, they entered the cash flow in levels form. This distinction is at the heart of using the level of the cash flow in order to find evidence of financially constrained investment.

Chirinko et al. (1999) found that the level of the cash flow had a large, positive, and significant effect on investment in a large sample of publicly traded U.S. firms from 1981-1991. They also found that, by controlling for financial constraints and accelerator effects, the elasticity of the user cost of capital, which includes the relative price of capital, the weighted average cost of capital, depreciation coverage, and tax incentives, was much smaller (-0.25) than the theoretical value of -1.0 assumed in the Hall-Jorgenson type of studies using Cobb-Douglas production functions and the flexible accelerator approach.

Two recent studies on the investment function by Spatareanu (2008) and Chirinko et al. (2011) also deserve mention in this survey. Spatareanu (2008) used a similar framework to that of Chirinko et al. (1999), but she focused on the difference in investment between high- and low-technology U.S. manufacturing firms. Her analysis covered the time period 1982 to 2001. In addition to the user cost, accelerator, and cash flow, she investigated the effects that stock prices may have had on firm investment. She found evidence for a significant effect of cash flow on investment; however, the effect tended to be much smaller than in Chirinko et al. (1999) and earlier studies of cash flow cited previously. Also, she concluded that stock price effects may be more important for new, young and innovative high-tech firms. In contrast to the findings of Chirinko et al. (1999), she found that the effect of changes in the user cost of capital on investment were not only small, but also mostly insignificant for U.S. manufacturing firms.[12] One potential reason for this finding, is that the timeframe of her study contains the computer revolution, which led to rapidly decreasing prices for computer-based capital assets, and the traditional measure of the user cost is determined with time-varying weights. As will be shown in Chapter 3, using such a weighting scheme in the face of large changes in relative price may have created a bias in the measurement of the user cost, and this bias can be controlled for using alternative sets of weights.

[12] She also found a large number of positive coefficients for the user cost elasticity.

Chirinko et al. (2011) re-visited their analysis of 1999 (using the same data set) and used interval-difference estimator techniques to find a more precise estimate of the elasticity of investment with respect to the user cost of capital. With this method, they emphasized low-frequency variation by creating intervals of average data and relied on this lower frequency data to reflect the long-run variation in the variables. Using this framework, they discarded the channel of liquidity constraints which focuses on short-run changes to investment decisions. Overall, they concluded that user cost elasticity is approximately -0.40 for publicly traded U.S. firms, which (in absolute value) is larger than their previous estimate, but still smaller than -1.0.

According to the theoretical model of Campa and Goldberg (1999), the real exchange rate is expected to be an important determinant of the desired capital stock of the firm in an open economy. The Campa and Goldberg framework, however, does not take into account the importance of either the accelerator or the user cost of capital, which are also expected to be important determinants of the desired capital stock of the firm, as found in the more general literature of the investment function. Other disconnects between the investment function literature and the work of Campa and Goldberg include their restrictive assumption of a one-period time-to-build for capital, which ignores the longer-term nature of fixed capital formation, and their inclusion of a simple interest rate instead of broad measure of the cost of capital, which accounts for changes in the relative price of capital. Furthermore, Campa and Goldberg (1999) did not control for potential financial or liquidity contraints, which may prevent a firm from investing as much as it had planned in order to meet its desired capital stock, and which was found by Blecker (2007) to be the primary channel through which the exchange rate effects investment in the aggregate U.S. manufacturing sector.

These issues suggest that a more open-ended model of the effect of the exchange rate on investment can provide a valuable robustness test for the results we obtain using the more restrictive Campa and Goldberg framework. The modeling framework of Chirinko et al. (1999) that combines the flexible accelerator approach with cash flow type indicators of liquidity constraints provides a workable framework into which the real value of the dollar can be introduced in alternate ways. In this framework, the growth rate of the real value of the dollar can be introduced in the same manner as sales growth and changes in the user cost of capital to investigate whether a dollar appreciation or depreciation affects investment through changes in the desired capital stock. In an alternate formulation, the level of the real value of the dollar can be introduced in the same manner as cash flow to investigate whether the value of the dollar affects the flow of investment in the short run, *i.e.*, the speed at which firms adjust their capital stocks to the desired level.

Using the Chirinko et al. (1999) approach to specifing the investment function and including the measure of the exchange rate in alternate ways will allow me to compare within a common modelling framework the different channels through which the exchange rate can affect investment, as identified by Campa and Goldberg (1999) and Blecker (2007). Admittedly, there is a drawback to using this approach in that the exchange rate might influence investment via already included variables such as sales growth and cash flow, which could suggest the presence of simultaneity issues. However, I will test for whether the exchange rate has any additional explanatory power in a model of investment that already controls for those variables, and I leave tackling this particular shortcoming to future research.

2.3 Conclusion

Overall, the majority of the previous research on the relationship between exchange rates and investment has tended to investigate the effect of the exchange rate on investment through its impact on the desired capital stock. The exchange rate affects the expected profitability of the firm or industry through the competitiveness of its products in different markets and the cost of the imported intermediate goods that it uses in production. One the one hand, currency appreciation makes domestic products less competitive both in export markets and relative to competing imports, which tends to reduce desired capital stocks and thereby to discourage investment for domestic firms. However, most of the research has focused mainly on the competitiveness of firms or industries in export markets and has put less emphasis on corresponding pressures from competing imports in the domestic market. On the other hand, currency appreciation lowers the cost of imported intermediate goods, which tends to encourage investment in firms or industries that rely heavily on such imports.

The investigation of the effect of the exchange rate on the desired capital stock is largely a product of the standard theoretical model developed by Campa and Goldberg (1999). Most of the more general literature on the investment function, however, relies upon the accelerator and the user cost of capital as the main determinants of the desired capital stock, and some of this literature also uses cash flow to test or control for financial/liquidity constraints. Although the empirical model of Campa and Goldberg (1999) does control for sales growth and interest rate changes, their model does not use the broader measure of the user cost of capital, which is standard in most investment models, and also does not take account of the possibility of financial constraints. As noted above, only two previous studies have tried to control for financial constraints in testing for exchange rate effects on investment.

In this study, therefore, I present two separate analyses of the effect of the exchange rate on investment in the U.S. manufacturing sector. First, in Chapter 4, I will apply the model of Campa and Goldberg (1999) to new and revised data and correct for various problems I have identified in their econometric approach. The large body of work by Goldberg (1990, 1993) and Campa and Goldberg (1995, 1997, 1999) on exchange rates and investment has ensured the prevalence of industry level analyses in that section of the literature. To my knowledge, this body of work is still the only industry level investigation of the effect of the exchange rate on investment in the U.S. Furthermore, these previous studies only take into consideration the period of dollar appreciation from 1979 to 1985 and the period of depreciation from 1985 to 1993. In addition, the hallmark study of Campa and Goldberg (1999) relies on the assumption of permanent changes in the exchange rate, which may mask the short-run effects found in the transitory component of exchange rate changes. Given the conflicting results in the recent research of Blecker (2007), Landon and Smith (2007), and Bahmani-Oskooee and Hajilee (2010), I re-investigate the effect of the real exchange rate on investment in the U.S. manufacturing sector, using improved econometric techniques as well as more recent and revised industry level data.

Certain limitations in the data available at the industry level limit the analysis to the basic framework of Campa and Goldberg. As discussed in the next chapter, the data necessary to construct a measure of the user cost are only available starting in 1987 and the corresponding data for industry level sales and investment are only available to 2005. The only available link between the two would be at the two-digit SIC level, which would yield a small panel of N=20 by T=18. Instead, I rely on the Campa and Goldberg framework in my industry level analysis in order to make comparisons to existing research. I contribute to the literature by updating the measure of imported input reliance to reflect more recent input-output tables and extend the period of analysis to 2005. In addition, I take more careful account of the effect of the exchange rate on the competitiveness of domestic goods that face pressure from competing imports. I also seek to determine the overall net effect of the exchange rate on investment by using industry-specific exchange rates, which has not been done previously in either section of the investment literature. And, as will be discussed in depth in Chapter 4, I find that Campa and Goldberg (1999) probably corrected for the wrong violations of classical least squares assumptions, and I use newer methods of panel data estimation to correct for the violations that I find, which are chiefly cross-sectional dependence and heteroskedasticity.

Second, in Chapter 5 I will provide the first analysis of the exchange rate on investment in the U.S. at the firm level. As noted above, most of the literature on investment functions in general, and especially the part that addresses financial constraints, is conducted using firm level data. However, most of the investment function literature is largely conducted within a closed-economy setting, which ignores the potential impact of the exchange rate on investment in a globalized setting. For comparability with the literature on exchange rates and investment and due to the availability of a large amount of data for U.S. manufacturing industries, I focus my efforts on firms in that sector. Because the vast majority of U.S. trade in goods consists in manufactured products, it makes sense to focus on the manufacturing sector in a first effort at identifying exchange rate effects on investment.

The much larger dataset used in the firm level analysis also provides an opportunity to build one more bridge across the gap between the literature on exchange rates and investment and the more general investment function literature. The theoretical model of Campa and Goldberg (1999) suggests that changes in the exchange rate can affect changes in the desired capital stock of a firm, and as noted above, there is empirical evidence supporting this relationship. The empirical analysis of Blecker (2007), however, suggests that the exchange rate may also affect the rate of investment via the channel of financial constraints, but Blecker only used aggregate data for the entire U.S. manufacturing sector. I test empirically which channel is more plausible by including the exchange rate in either growth rate or level form in a more open-ended investment model of the type used by Chirinko et al. (1999). Using this framework generates a more general empirical specification which allows for multiple and differing lags for the determinants of investment, and more correctly controls for the user cost of capital and cash flow type liquidity constraints.

CHAPTER 3

DATA

This chapter is divided into two main sections that discuss the data used for the analyses performed at the industry level and the firm level. For the section regarding the data used in the industry level analysis, I include a subsection on the data used for replication purposes with a detailed discussion of permanent exchange rates, and a subsection describing the extended dataset used in the current analysis. I close the industry level portion with a subsection on unit root tests.

For the section regarding the data used in the firm level analysis, I take a slightly different approach, because the data used for replication is also used in my extended analysis, where I introduce the exchange rate into a firm-level investment function. The exchange rate series used in the firm level analysis are also used in the industry level analysis, so I provide a brief review. I include detailed subsections, however, for the construction of the user cost variables and the firm level data. I close the firm level portion with a subsection on unit root tests.

3.1 Industry Level Data

The data used in the industry level analysis are compiled from a variety of sources. They include extensive industry level trade and production data for U.S. manufacturing industries. They also include various measures of real exchange rates for the overall U.S. economy and at the industry level. A full description of the data used in both the replication and extension portions of the industry level analysis follows.

3.1.1 Replication

The study chosen for replication is that of Campa and Goldberg (1999), in which the authors develop annual, industry level data for 20 two-digit SIC (1972) U.S. manufacturing sectors from 1972-1993. The data for that analysis are presented in greater detail in Campa and Goldberg

(1997), and much of it is an extension of the dataset used in Campa and Goldberg (1995), which covers the time period from 1972-1986.

The first aspect of the data used in the industry level analysis is the construction of the measures of external orientation. These measures are designed to capture different avenues by which industries face exchange rate exposure. They are determined in a panel data setting and are indexed by industry, i, and annual time period, t. The first measure is the export share, χ_t^i, which is the ratio of industry export revenues to industry shipments. The second measure is the import share, m_t^i, which is the ratio of imports to domestic consumption, where domestic consumption is defined as imports plus new domestic supply. In Campa and Goldberg (1995, 1997, 1999), the source of the data for the export and import shares is the U.S. Department of Commerce with the SIC codes on a 1972 basis, but the original data for the time period covered by those studies are no longer available. Also, it is not clear whether Campa and Goldberg differentiate between import/export-based SIC codes (MSIC/XSIC) and domestic SIC codes in formulating their data series. According to Feenstra (1996, 1997) and Feenstra et al. (2002), there are significant differences in the two types of data, and the domestic SIC data would not have been available without a notable concordance with the trade data. The domestic SIC trade data crafted by Feenstra utilize a series of rigorous concordances in determining the trade flows associated with domestic industries. The Feenstra trade data are available online from the Center for International Data at UC Davis.[1] For the purpose of replication, I start with the multilateral U.S. import and export data according to the 4-digit SIC (1972), which is available from 1958-1994. The data for imports, exports and industry shipments are then aggregated to the two-digit SIC (1972) level to calculate the industry-specific export and import shares.

The final measure of external orientation is the imported input share, α_t^i. The construction of the imported input share series combines information on production technology from input-output tables with data on import penetration to estimate the share of imported inputs in the total value of production for each two-digit SIC manufacturing industry. The imported input share is defined as

$$\alpha_t^i = \frac{\sum_{j=1}^{n-1} m_t^j p_{\bar{t}}^j q_{j,\bar{t}}^i}{\left(\sum_{j=1}^{n-1} p_{\bar{t}}^j q_{j,\bar{t}}^i\right) + p_t^n q_{n,t}^i} \tag{3.1}$$

where i is the index representing the output industry and j is the index representing the production input industry. The share of imports in total domestic consumption for industry j in period t is m_t^j.

[1] The data can be downloaded at `http://cid.econ.ucdavis.edu/`.

The value of inputs from industry j used in production by industry i in period $\bar{t}$ is $p^j_{\bar{t}} q^i_{j,\bar{t}}$, and the annual wage bill for industry i in period t is $p^n_t q^i_{n,t}$. The total number of product inputs is n with the nth input being labor. The total for the denominator reflects the value of total production cost for industry i in period t. In general, the imported input share weights each manufacturing input by that input's import share, resulting in an import cost to total cost of production ratio. This ratio attempts to estimate the actual exposure of the industry to changes in the cost of imported intermediaries.

In order to construct the imported input series, three major assumptions are necessary due to limitations in the data. First, the inputs other than labor are limited to only manufacturing inputs, which ignores commodity and service inputs. In addition, all labor is assumed to be supplied domestically. Second, the value used for m^j_t is the aforementioned import share, which reflects the sum of household and commercial consumption of the imported product input. As noted in Campa and Goldberg (1995), a more appropriate measure would be that of business imports divided by business consumption, but that data is not available. Last of all, the construction of the imported input series requires the assumption of a single technology matrix because of the lack of accurate, annual input-output (I-O) accounts for the overall U.S. economy. Instead, a single year of the benchmark I-O accounts produced by the Bureau of Economic Analysis (BEA) is chosen to reflect the production technology for all years. Using these fixed input-ouput coefficients over a long time period is imperfect, however, because it ignores the potential for substitutability of factors of production and changes in technology.

The values for $p^j_{\bar{t}} q^i_{j,\bar{t}}$ are derived from the 1982 Benchmark I-O accounts published by the BEA, which sets $\bar{t} = 1982$. The original source data is categorized by 6-digit I-O codes, which are converted to the equivalent 4-digit SIC (1972) using the concordance of Campa and Goldberg (1995).[2] These values are then aggregated to the 2-digit SIC level. The wage bill, $p^n_t q^i_{n,t}$, is taken from the NBER-CES Manufacturing Industry Database[3], which is a joint effort between the National Bureau of Economic Research (NBER) and the U.S. Census Bureau's Center for Economic Studies (CES). This source contains annual, industry-level data on output, employment, payroll and other input costs, investment, capital stocks, total factor productivity (TFP) and various price deflators. It covers all 4-digit manufacturing industries from 1958-1996 for 1972-based SIC codes. This database is constructed in accordance with Bartelsman and Gray (1996) in order to match up

[2]The concordance is published online at `http://fmwww.bc.edu/ec-p/data/nbercd2/io_table.html`.

[3]The data can be downloaded at `http://www.nber.org/nberces/`.

Table 3.1. Measures of External Exposure for U.S. Manufacturing Industries, 1985. Comparison to the Benchmark Study: (a) Actual Data, (b) Benchmark Data.

SIC	Industry name	Export Share, χ (a)	Export Share, χ (b)	Import Share, m (a)	Import Share, m (b)	Imported Input Share, α (a)	Imported Input Share, α (b)
20	Food and kindred products	3.3	3.6	4.5	4.3	4.1	3.6
21	Tobacco products	6.9	8.1	0.5	0.5	1.8	1.6
22	Textile mill products	3.2	3.6	10.5	7.7	6.9	5.4
23	Apparel and other textiles	1.6	1.8	20.9	22.4	10.1	2.3
24	Lumber and wood products	4.9	5.3	10.2	10.5	6.6	3.5
25	Furniture and fixtures	1.5	1.6	9.5	9.2	5.8	5.3
26	Paper and allied products	4.2	4.3	7.9	7.1	5.8	5.1
27	Printing and publishing	1.1	1.2	1.2	1.2	3.4	3.0
28	Chemicals and allied products	11.0	11.7	7.1	6.5	5.4	4.5
29	Petroleum and coal products	3.0	3.1	9.9	9.5	8.0	6.8
30	Rubber and miscellaneous products	3.9	3.9	6.9	6.3	4.6	3.9
31	Leather and leather products	5.6	6.1	50.6	49.6	17.6	15.7
32	Stone clay and glass products	3.3	3.4	8.2	7.6	4.3	3.6
33	Primary metal products	4.3	3.7	17.5	16.6	10.3	9.2
34	Fabricated metal products	4.1	4.7	5.2	5.5	8.3	7.8
35	Industrial machinery and equipment	17.7	20.1	16.0	13.9	8.4	7.2
36	Electronic and other electric equipment	9.7	10.1	18.1	17.0	7.7	6.7
37	Transportation equipment	12.5	13.0	20.3	18.4	9.9	10.7
38	Instruments and related products	14.1	15.5	14.8	13.7	6.6	5.4
39	Other manufacturing	6.7	8.1	32.1	35.0	9.4	8.5

Notes: Measures of external exposure are reported in percentage terms. The benchmark results are published in Campa and Goldberg (1997).

with the Feenstra trade data at the industry level. The nominal payroll data is aggregated to the 2-digit SIC (1972) level, and then converted to a constant dollar (1982) wage bill using Producer Price Index (PPI) data from the Federal Reserve Bank of St. Louis database (FRED).[4]

In Table 3.1, I report the results for the three measures of external exposure in 1985 along with a comparison to the values reported in Campa and Goldberg (1997). Although I do not have the exact data used by Campa and Goldberg, my efforts at reproduction result in values that are of the same order of magnitude as those of the benchmark study. One notable exception, however, is the imported input share for SIC 23, apparel and other textiles. I find a value of α for SIC 23 in 1985 that is equal to 10.1%, whereas, in Campa and Goldberg (1997) the authors report a value of 2.3%. In Campa and Goldberg (1995), the authors report the value for α for apparel and other textiles in 1982 as 4.55%. Given that the majority of the manufacturing inputs for apparel and

[4]The data can be downloaded at `http://research.stlouisfed.org/fred2/series/PPIFGS?cid=31`.

other textiles in the 1982 Benchmark I-O accounts come from SIC 22 and 23 (SIC 22 is textile mill products), and both industries are faced with a rising import share during that time period; it is quite surprising that the imported input share would decline from 1982 to 1985 as reported by Campa and Goldberg.

The NBER-CES database is also the source for industry investment, sales (value of shipments), the deflators for investment and sales (1987=1.00), and the data used to construct the price-over-cost markups. The original 4-digit SIC (1972) data for investment and sales are converted to real (1987) values using their respective deflators and then aggregated to the 2-digit SIC level. Both the real investment[5] (I) and real sales (y) series are industry-specific and time-varying for 1972-1993. To construct the markup measure, I follow Campa and Goldberg (1999), and define the average 2-digit SIC industry markup, $\tilde{\kappa}_t^i$, as

$$\tilde{\kappa}_t^i = \frac{\text{value added} + \text{cost of materials}}{\text{payroll} + \text{cost of materials}} \tag{3.2}$$

where each component is first aggregated to the 2-digit SIC level. Again, the average markup series is industry-specific and time-varying for 1972-1993.

Campa and Goldberg (1999) include two additional control variables in the investment function estimation: the real price of oil and an interest rate. The real price of oil is used as a proxy to control for the cost of other inputs. The source for the oil price data is the U.S. Energy Information Administration,[6] which provides a data series for annual real oil prices. The original source data is converted to real 1987 prices to match that of real investment and real sales. The estimate of the cost of capital used by Campa and Goldberg (1999) is the nominal interest rate on the 10-year Treasury note. The source for this data is FRED,[7] and reflects an annual average of monthly figures for the 10-year Treasury note at a constant maturity rate. Both the real price of oil and the interest rate are time-varying from 1972-1993, but they do not vary by industry.

The final data series used in the replication is the real exchange rate. In Campa and Goldberg (1999), the authors use the real exchange rate series *reu* from the International Financial Statistics (IFS) database produced by the International Monetary Fund (IMF). The IMF discontinued the *reu* series with the March 2010 release of the IFS, (IMF, 2011). The *reu* series used here was

[5]In both the 1995 and 1999 papers, Campa and Goldberg are never very clear as to whether they use nominal or real investment in their empirical analyses. I assume that they use real investment.

[6]The data can be downloaded at `http://www.eia.doe.gov/emeu/steo/realprices/index.cfm`.

[7]The data can be downloaded at `http://research.stlouisfed.org/fred2/series/GS10?cid=105`.

downloaded from the IFS before the discontinuation, and the data was only available from 1975q1. The *reu* series for the real effective exchange rate is based on relative normalized unit labor costs. In Campa and Goldberg (1999), the authors likely chose this real exchange rate series, because they were comparing exchange rate effects across four different countries (the U.S., U.K., Canada and Japan), and they wanted a common source for the exchange rate data. Since the *reu* series does not cover the entire period of the replication (1972-1993), and because I am only investigating one country, I also use the broad trade-weighted real dollar index from the Federal Reserve Board (Statistical Release H.10).[8] This exchange rate series is the real, broad index of the value of the U.S. dollar with March 1973 = 100, and is available starting in January 1973. The monthly data are converted to quarterly averages, which are used in the derivation of the permanent component of exchange rate changes as described in greater detail below.

Permanent exchange rates

In their theoretical model, Campa and Goldberg (1999) assume that exchange rate changes are permanent and uncorrelated over time. As a result, they decompose the real exchange rate series into permanent and transitory components and use only the permanent component in their empirical work. The method chosen is the univariate decomposition performed on the log of the real exchange rate index, as suggested in Beveridge and Nelson (1981). For the log of the real exchange rate, e_t, the Beveridge-Nelson procedure yields the following expression: $e_t = \tilde{e}_t + \hat{e}_t$, where $\tilde{e}_t$ is the transitory component and $\hat{e}_t$ is the permanent component. The transitory component is a stationary process defined by

$$\tilde{e}_t = -E_t\left(\sum_{j=1}^{\infty} \Delta e_{t+j} \middle| \Delta e_t, \Delta e_{t-1}, \ldots\right) \tag{3.3}$$

and the permanent component is a random walk defined by

$$\hat{e}_t = e_t + E_t\left(\sum_{j=1}^{\infty} \Delta e_{t+j} \middle| \Delta e_t, \Delta e_{t-1}, \ldots\right) \tag{3.4}$$

In practice, Campa and Goldberg assume that the first differences of the quarterly log real exchange rate follow an $AR(4)$ process. Attempting to replicate this approach was somewhat problematic. The only benchmark available for comparison is the variance of exchange rates accounted

[8]The data can be downloaded at `http://www.federalreserve.gov/releases/h10/summary/indexbc_m.htm`.

for by temporary shocks.[9] Campa and Goldberg define this ratio as $\text{var}(\tilde{e}_t) / \text{var}(e_t)$. If that is the correct ratio for comparison, then my results from the Beveridge-Nelson (B-N) decomposition are quite different. On the other hand, previous studies of exchange rate decomposition (which are referenced by Campa and Goldberg) use a different ratio for this measure. The studies by Huizinga (1987) and Clarida and Gali (1994) define the ratio as $\text{var}(\Delta\tilde{e}_t) / \text{var}(\Delta e_t)$. When performing their econometric analysis, Campa and Goldberg use the permanent component expressed in differences ($\Delta\hat{e}$), which might suggest that the ratio reported is actually measured in difference form. The results for both ratios are presented in Table 3.2, and are strictly used for comparison to the results presented in the benchmark study.

Table 3.2. Ratio of Variances of Transitory Component to Actual Exchange Rate

Method	Period	Source	$\text{var}(\tilde{e}_t) / \text{var}(e_t)$	$\text{var}(\Delta\tilde{e}_t) / \text{var}(\Delta e_t)$
(Campa and Goldberg, 1999)				
Beveridge-Nelson	1972-1993[a]	IFS (reu)	0.403[b]	
Beveridge-Nelson	1975q1-1993q4	IFS (reu)	0.054	0.627
Hodrick-Prescott	1975q1-1993q4	IFS (reu)	0.137	0.846
Beveridge-Nelson	1973q1-1993q4	Fed (H.10)	0.074	0.401
Hodrick-Prescott	1973q1-1993q4	Fed (H.10)	0.178	0.864
Beveridge-Nelson	1973q1-2005q4	Fed (H.10)	0.069	0.371
Hodrick-Prescott	1973q1-2005q4	Fed (H.10)	0.165	0.868

[a] Campa and Goldberg (1999) only report that they use quarterly data from 1972-1993. They do not report which quarters are used.
[b] I am not completely certain whether the ratio reported in the benchmark study is measured in levels or differences.

The result of the B-N procedure using the available IFS data that most closely resembles that of Campa and Goldberg (1999) is 0.054, which is very different from the benchmark result of 0.403. Using the variance of differences ratio, as in Huizinga (1987) and Clarida and Gali (1994), the result is much closer at 0.627. Interestingly, when using the Federal Reserve's trade-weighted broad index of the real dollar (series H.10) for the comparable time period, the result of the variance of differences ratio is 0.401.

One possible scenario is that Campa and Goldberg misstated the ratio that they used for the measure of variance of exchange rates accounted for by temporary shocks. Given such a scenario, it

[9] To report either ratio as "the variance of exchange rates accounted by temporary shocks" is a bit misleading, since it does not consider the covariance between the measure of the exchange rate and the equivalent measure of the transitory component.

appears that the real exchange rate series used by Campa and Goldberg yields remarkably similar results for the B-N decomposition to that of the broad, trade-weighted index of the Fed over the comparable time period. Another scenario is that Campa and Goldberg state the correct ratio, and I am unable to replicate their results for the B-N decomposition.

Given the possibility of the second scenario, I also performed the Hodrick-Prescott (H-P) decomposition on the log of both exchange rate series. The H-P filter, as developed by Hodrick and Prescott (1997), decomposes the log of the real exchange rate series, e_t, into a trend, $\hat{e}_t$, and a stationary component, $\tilde{e}_t = e_t - \hat{e}_t$. The decomposition occurs by choosing $\hat{e}_t$ such that the following sum of squares is minimized:

$$\frac{1}{T}\sum_{t=1}^{T}(e_t - \hat{e}_t)^2 + \frac{\lambda}{T}\sum_{t=2}^{T-1}\left[(\hat{e}_{t+1} - \hat{e}_t) - (\hat{e}_t - \hat{e}_{t-1})\right]^2 \tag{3.5}$$

where λ is a constant[10] that penalizes the incorporation of fluctuations into the trend and T is the number of usable observations. The results for the H-P decomposition of the IFS and Fed series are very different from the benchmark, no matter which variance ratio is used. Overall, the ratios measured in differences from the B-N decompositions are of the same order of magnitude as that reported in the benchmark, while those measured in levels or those derived from the H-P filter are not.

Lastly, I also report the results of both decompositions for the real exchange rate series that is used in the extended analysis (1973q1-2005q4). A detailed description of all the data used in the extension portion of the industry level analysis is found in the next section.

3.1.2 Extended Dataset

In my extension of the industry level analysis of exchange rates and investment, I start with the basic framework of Campa and Goldberg (1999) and create a new dataset that extends the period of analysis by twelve years. In so doing, I make several changes to the underlying structure of the data. These changes and the construction of the new dataset are described in detail in this subsection.

The beginning of the time series component for the panel dataset is 1973, which is based upon the availability of real exchange rate data for the U.S.. The end of the time series component is constrained to 2005 for reasons that will be explained in more detail below. Based on the analysis

[10]For all reported H-P decompositions, $\lambda = 1600$ which is the common value associated with quarterly data (see for example Ravn and Uhlig (2002)).

in the previous section, the real exchange rate variable that is chosen is the broad trade-weighted real dollar index from the Federal Reserve Board (Statistical Release H.10). As noted before, this exchange rate series is the real, broad index of the value of the U.S. dollar, so an increase (decrease) represents a USD appreciation (depreciation) relative to a large group of major U.S. trading partners. The monthly data from the Fed are converted to quarterly averages, which are used in the derivation of the permanent component of exchange rate changes as described in the previous subsection. I also convert the monthly data into annual averages in order to create an actual real exchange rate series. The actual real exchange rate series and the permanent component from the H-P filter are annual data from 1973-2005. By construction, the permanent component from the B-N decomposition loses the first annual observation so the time period is from 1974-2005.

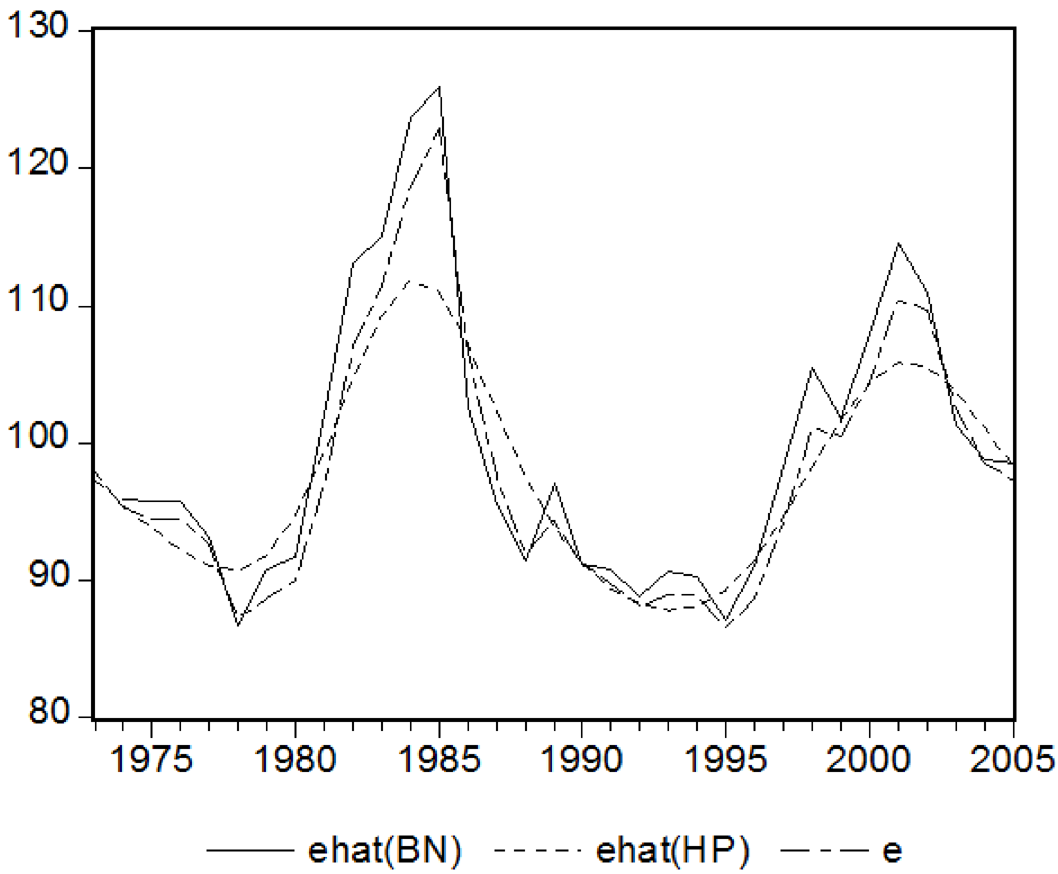

Figure 3.1. Actual and Permanent Components of the Real, Broad Index of the Value of the U.S. Dollar: Annual Averages, 1973-2005

In Figure 3.1, I present the annual time series for all three measures of the real exchange rate. First, one should note that the HP filtered series is much smoother than the BN "permanent" series, which tracks the actual real value of the dollar much more closely. Rather mysteriously, the permanent component according to the BN decomposition seems to lead the actual value in the upswings. Since 1993, which is the final year of the benchmark analysis, the real value of the dollar experienced a general period of appreciation from 1995 to a peak in 2001, followed by a subsequent period of depreciation to 2005. Since 1982, which is the year used in the benchmark for the technology matrix, the real value of the dollar continued to appreciate to its all-time high in 1985 and then experienced a general period of depreciation until 1995. Given the large swings in the value of the dollar since 1982, manufacturing industries likely updated their production technologies in response to price changes that were influenced by changes in the real exchange rate. As a result, I update the input-output matrix to reflect manufacturing production in 2002.

Before discussing the construction of the updated input-output matrix, though, I will describe three additional measures of the real exchange rate that are included in the extended analysis. Goldberg (2004) developed industry-specific exchange rates for the U.S. These real effective exchange rate indexes are constructed in a similar manner to the broad index of the Fed, except that they use an industry-specific export and import weighting scheme. Instead of constructing a single aggregate measure for the entire U.S. economy, which is based on total trade activity, the industry-specific total trade weighted exchange rates (ter_t^i) are weighted by export and import activity for each individual industry. Two additional exchange rate series are weighted by export activity to achieve an export-weighted rate (xer_t^i) and by import activity to achieve an import-weighted rate (mer_t^i), both of which are industry-specific. All three industry-specific real exchange rate series are available from the Federal Reserve Bank of New York (FRBNY) on an annual basis for 1972-2005.[11] The original source data is organized by NAICS codes, but I utilize the concordance provided with the data to convert it to the 2-digit SIC level.

To construct the updated input-output matrix, I start with the 2002 Benchmark I-O accounts published by the BEA. In order to be able to compare my results to both Campa and Goldberg (1999) and Blecker (2007), I limit the analysis to manufacturing industries. I assume that product inputs are limited to manufactured inputs and domestically supplied labor, as in Campa and Goldberg (1999). The data in the benchmark I-O accounts are organized by I-O codes. In order

[11] The data can be downloaded at `http://www.newyorkfed.org/research/global_economy/industry_specific_exrates.html`.

to combine the production technology with trade data and industry specific data, I develop a concordance between the 2002 6-digit I-O codes and 2-digit 1987 SIC codes. A detailed description of the concordance can be found in Appendix 3.A.

I choose 1987 SIC codes as the industry basis because of the availability of trade data and industry level data that are rigorously concorded to that common classification scheme. The source of the trade data is Schott (2008),[12] who uses a similar concordance methodology to that of Feenstra (1996, 1997) and Feenstra et al. (2002). This data includes import, export and shipments data for U.S. manufacturing industries at the 4-digit SIC (1987) level. In addition, the Schott data are designed to match up with the 1987 SIC version of the NBER-CES Manufacturing Industry Database. Both the Schott trade data and the NBER-CES manufacturing industry data are only available up to 2005, which sets the limit for the time series component of the analysis.

Using the same methodology as Campa and Goldberg (1999), which is described in the replication section above, I use the I-O, trade and NBER-CES data to construct measures of external orientation from 1972-2005 at the 2-digit SIC (1987) level. In order to use the Schott trade data, I first aggregate the 4-digit SIC (1987) values for exports, imports and shipments up to the 2-digit SIC (1987) level. After aggregation, I calculate the export share, χ_t^i, and import share, m_t^i, for each 2-digit manufacturing industry. In order to calculate the industry level imported input share, α_t^i, I use the same formula as defined in Equation (3.1). In the extended analysis, however, $\bar{t} = 2002$ to reflect the updated technology matrix, which is based upon the 2002 Benchmark I-O accounts. The import share used is the updated m_t^i from the Schott trade data, and the wage bill is from the 1987 SIC version of the NBER-CES data. The original 4-digit SIC (1987) payroll data is first aggregated to the 2-digit SIC level, and then it is converted to constant 2002 dollars using PPI data from FRED.

In Figure 3.2, I plot the three measures of external orientation for each manufacturing industry from 1973-2005. The most striking change to the measures of industry exposure is found in the steady rise in the share of imported goods in domestic consumption. This rise is particularly pronounced in the industries of apparel, furniture and fixtures, leather, electrical machinery and miscellaneous manufactured goods, where imports made up over 50% of domestic consumption as of 2005. With the exception of apparel, these industries have also experienced a general rise in the export share; however, the rise has been at a lesser overall rate. All five industries have also

---

[12]The data can be downloaded at `http://www.som.yale.edu/faculty/pks4/sub_international.htm`.

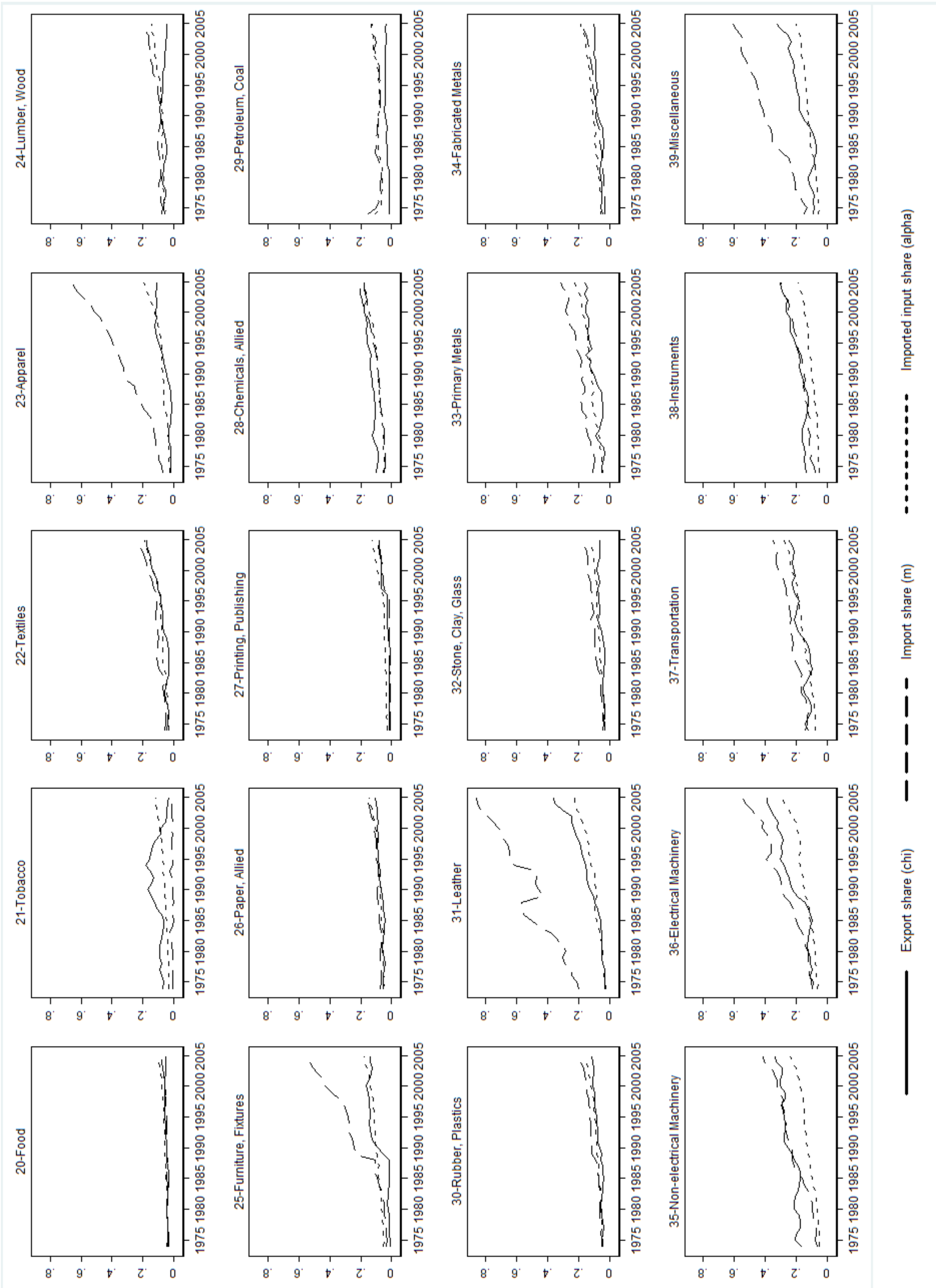

Figure 3.2. External Exposure by Industry, 1973-2005

experienced a slow, steady rise in the imported input share. A similar, though less dramatic, pattern exists for primary metals, non-electrical machinery, transportation equipment and instruments, for which imports made up over 25% of domestic consumption as of 2005.

Since I start the extended analysis with a modified version of the Campa and Goldberg (1999) framework, I also use the 1987 SIC version of the NBER-CES database as the source for industry investment, sales (value of shipments), the deflators for investment and sales (1987=1.00), and the data used to construct the price-over-cost markups. The original 4-digit SIC (1987) data for investment and sales are converted to real (1987) values using their respective deflators and then aggregated to the 2-digit SIC level. Both the real investment (I_t^i) and real sales (y_t^i) series are industry-specific and time-varying for 1972-2005. Using Equation (3.2), I compute the average markup series, where each component is first aggregated to the 2-digit SIC (1987) level. The average markup is industry-specific and time-varying for 1972-2005.

Table 3.3. Summary Statistics for the Markup Variable

SIC	Industry name	Mean	Std. Dev.	Min	Max
20	Food and kindred products	1.39	0.1106	1.23	1.58
21	Tobacco products	3.27	1.5520	1.57	6.36
22	Textile mill products	1.30	0.0414	1.22	1.39
23	Apparel and other textiles	1.39	0.0402	1.29	1.44
24	Lumber and wood products	1.28	0.0359	1.20	1.37
25	Furniture and fixtures	1.40	0.0440	1.32	1.48
26	Paper and allied products	1.42	0.0692	1.32	1.54
27	Printing and publishing	1.61	0.0952	1.49	1.79
28	Chemicals and allied products	1.69	0.1260	1.48	1.88
29	Petroleum and coal products	1.16	0.0554	1.06	1.29
30	Rubber and miscellaneous products	1.44	0.0410	1.36	1.51
31	Leather and leather products	1.38	0.0460	1.31	1.50
32	Stone clay and glass products	1.52	0.0799	1.40	1.66
33	Primary metal products	1.28	0.0673	1.14	1.40
34	Fabricated metal products	1.39	0.0445	1.34	1.48
35	Industrial machinery and equipment	1.43	0.0274	1.38	1.49
36	Electronic and other electric equipment	1.54	0.1115	1.38	1.75
37	Transportation equipment	1.30	0.0379	1.25	1.37
38	Instruments and related products	1.67	0.0768	1.54	1.80
39	Other manufacturing	1.48	0.0463	1.40	1.57
All industries, pooled		1.52	0.5475	1.06	6.36
All industries, except Tobacco		1.43	0.1508	1.06	1.88

In Table 3.3, I present summary statistics for the markup variable. These statistics clearly indicate that there is something different about the data used in the construction of the markup for SIC 21, tobacco products. The equivalent mean value of the markup for the tobacco industry from

1972-1986, as reported in Campa and Goldberg (1995), is 1.44, which is less than the minimum value reported here (1.57). In addition, the large standard deviation (1.5520) is more than ten times greater than the value for any other industry. These stark differences in the markup variable statistics for the tobacco industry and the remaining U.S. manufacturing industries is likely due to tax considerations. Since its markup is so drastically different from the other industries, I choose to drop the tobacco industry from the extended analysis.[13]

Control variables

For comparison to Campa and Goldberg (1999), I include the real price of oil and an interest rate as control variables in the investment function of the extended analysis. As in the replication portion of the analysis, the source of the oil price data is the U.S. Energy Information Administration and the original data are converted to real 1987 prices. Campa and Goldberg's choice of the nominal 10-year Treasury note as the estimated cost of capital seems somewhat arbitrary. Using a long term rate makes sense, but, theoretically, real investment is dependent on a real measure of the cost of capital. To test the sensitivity of the results to the choice of interest rate, I also run regressions using the real 10-year Treasury note and the nominal and real values of Moody's seasoned Aaa corporate bond yield. The nominal rates were taken from FRED, and I used an annual average of monthly data. The nominal interest rates were then converted to real rates using inflation rates from the BEA.[14] Both the real price of oil and the interest rate are time-varying from 1972-2005, but they do not vary by industry.

Unit root tests

To test the stationarity of the data used in the industry level analysis, I perform a series of unit root tests. First, I investigate the aggregate level data in a time series setting. Then, I investigate all industry level variables used in the regressions in a panel data setting.

For the time series unit root tests, I choose the Phillips-Perron (PP) tests outlined in Phillips and Perron (1988). The PP test without a trend tests for the presence of a random walk without drift, and the PP test with a trend tests for a random walk with or without drift. For the real price of oil and the actual and permanent components of the real, broad index of the value of the U.S.

---

[13] In the replication dataset, the tobacco industry is still included, because that data does not display any abnormalities. In a similar fasion to outlier treatment, I only remove it from the extended data set to avoid biasing the results.

[14] The inflation data is from Table 1.1.7, Percent Change from Preceeding Period in Prices for Gross Domestic Product (Chain-type price index for GDP) The data can be downloaded at `http://www.bea.gov/national/nipaweb/SelectTable.asp`.

Table 3.4. Phillips-Perron Time Series Unit Root Tests, 1974-2005

H_o: Variable contains a unit root. H_a: Variable is stationary.

	Levels			Differences		
Variable[a]	Trend	Z_t	p-value[b]	Trend	Z_t	p-value[b]
$\hat{e}_t$	No	-2.170	0.2174	No	-4.000	0.0014
	Yes	-2.143	0.5222	Yes	-3.927	0.0111
e_t	No	-2.066	0.2583	No	-3.154	0.0228
	Yes	-2.053	0.5720	Yes	-3.095	0.1074
oil_t	No	-1.523	0.5222	No	-5.273	0.0000
	Yes	-1.223	0.9058	Yes	-5.367	0.0000
T-note	No	-0.995	0.7552	No	-4.645	0.0001
	Yes	-2.306	0.4304	Yes	-4.665	0.0008
real T-note	No	-2.201	0.2060	No	-4.915	0.0000
	Yes	-1.765	0.7213	Yes	-5.830	0.0000
Aaa	No	-0.989	0.7572	No	-3.933	0.0018
	Yes	-2.093	0.5500	Yes	-3.979	0.0094
real Aaa	No	-2.172	0.2166	No	-4.561	0.0002
	Yes	-1.447	0.8467	Yes	-5.457	0.0000

[a] The B-N permanent component of the real exchange rate ($\hat{e}$), the actual real exchange rate (e), and the real price of oil (oil) are all measured in natural logs.

[b] MacKinnon approximate p-values. Three Newey-West lags used in calculating the standard errors, as determined by the plug-in estimator, $4(T/100)^{2/9}$.

dollar, I perform the PP tests on the log levels and log differences of each variable. For the four different interest rate series, I perform the tests on the levels and differences of each variable.

The results of the time series unit root tests are presented in Table 3.4. These results suggest that all of the aggregate level variables contain a unit root, when measured in levels. By differencing the data, however, the unit roots are removed from the data with the exception of the actual exchange rate series. Because the actual and permanent component of the exchange rate variables only enter into the regressions after being combined with other industry level variables, I test those different combinations with panel data unit root tests.

For the panel data unit root tests, I choose the Levin-Lin-Chu (LLC) tests outlined in Levin et al. (2002). The Levin-Lin-Chu (LLC) tests are recommended for panels of moderate size with a minimum of 10 panels and 25 observations per panel. The tests are run using the Aikaike information criterion for the lag selection and are run with and without a trend. These tests are also run on demeaned data, which first subtract the cross-sectional averages from each series. Levin et al. (2002) recommend using this option to mitigate the impact of cross-sectional dependence.

Table 3.5. Levin-Lin-Chu Panel Data Unit Root Tests[a], 1974-2005

H_o: Panels contain unit roots. H_a: Panels are stationary.

	Actual Data			Demeaned Data		
Variable[b]	Trend	Adj. t^*	p-value	Trend	Adj. t^*	p-value
ΔI_t^i	No	-19.8757	0.0000	No	-18.6002	0.0000
	Yes	-17.3789	0.0000	Yes	-16.3139	0.0000
Δy_t^i	No	-17.4579	0.0000	No	-14.2714	0.0000
	Yes	-16.6687	0.0000	Yes	-14.8856	0.0000
$(\tilde{\kappa}_t^i)^{-1}\Delta\hat{e}_t$	No	-13.6275	0.0000	No	-14.6150	0.0000
	Yes	-11.2755	0.0000	Yes	-12.3608	0.0000
$\chi_t^i(\tilde{\kappa}_t^i)^{-1}\Delta\hat{e}_t$	No	-13.6875	0.0000	No	-14.2157	0.0000
	Yes	-11.3324	0.0000	Yes	-11.7218	0.0000
$\alpha_t^i(\tilde{\kappa}_t^i)^{-1}\Delta\hat{e}_t$	No	-13.8454	0.0000	No	-14.9051	0.0000
	Yes	-11.5050	0.0000	Yes	-12.4954	0.0000
$(\tilde{\kappa}_t^i)^{-1}\Delta e_t$	No	-9.0719	0.0000	No	-10.0603	0.0000
	Yes	-6.9900	0.0000	Yes	-8.0352	0.0000
$\chi_t^i(\tilde{\kappa}_t^i)^{-1}\Delta e_t$	No	-9.0272	0.0000	No	-9.6100	0.0000
	Yes	-6.9659	0.0000	Yes	-7.6193	0.0000
$\alpha_t^i(\tilde{\kappa}_t^i)^{-1}\Delta e_t$	No	-9.1498	0.0000	No	-10.2261	0.0000
	Yes	-7.1154	0.0000	Yes	-8.0853	0.0000
$(m_t^i)\Delta e_t$	No	-9.1640	0.0000	No	-9.7221	0.0000
	Yes	-7.0970	0.0000	Yes	-7.6076	0.0000
$(\chi_t^i)\Delta e_t$	No	-9.0070	0.0000	No	-9.1080	0.0000
	Yes	-6.9534	0.0000	Yes	-7.1383	0.0000
$(\alpha_t^i)\Delta e_t$	No	-9.0522	0.0000	No	-10.4280	0.0000
	Yes	-7.0319	0.0000	Yes	-8.3095	0.0000
Δter_t^i	No	-6.4558	0.0000	No	-3.0057	0.0013
	Yes	-4.6347	0.0000	Yes	-2.1223	0.0169
Δxer_t^i	No	-6.6663	0.0000	No	-4.2136	0.0000
	Yes	-4.5090	0.0000	Yes	-5.2999	0.0000
Δmer_t^i	No	-5.5144	0.0000	No	-3.2422	0.0006
	Yes	-4.5957	0.0000	Yes	-2.4508	0.0071

[a] The number of lags for each panel is chosen by minimizing AIC criteria, and the asymptotics for each test require $N/T \to \infty$.

[b] Δ indicates the variable is measured in log differences, and $\hat{e}$ is the B-N permanent component of the real exchange rate.

The results of the panel data unit root tests are presented in Table 3.5. These results show no evidence of nonstationarity present in any of the regression variables used in the extended analysis.

Although the log difference of the actual exchange rate series showed evidence of containing a unit root in the times series tests, when interacted with industry level measures of exposure and/or markups, the combined variables show evidence of stationarity in the panel data setting. In addition, the three industry-specific exchange rate series, show no evidence of containing unit roots when measured in log differences.

3.2 Firm Level Data

The data used in the firm-level analysis is also compiled from a variety of sources. To form the user cost series, I use extensive asset-specific data for industry level investment, capital stocks and capital goods. I also derive a large firm level dataset, which includes firm data on investment, capital, sales and cash flows. A full description of the user cost formulation and the firm level data are included in subsections below.

For econometric reasons discussed in Chapter 5, I cannot use the broad trade-weighted real dollar index from the Fed or any other aggregate exchange rate index that varies only with time in the firm-level estimates. Instead, I use the three, annual, industry-specific real exchange rate series originally developed by Goldberg (2004) and now available from the FRBNY, as discussed in the previous section on industry-level data: the total trade-weighted exchange rate (ter), the export-weighted exchange rate (xer) and the import-weighted exchange rate (mer). Each of these series are industry-specific and time-varying from 1974-2010. The industry-specific exchange rates are matched to the user cost and firm level data based on two-digit SIC codes. To keep the scale of the exchange rate series consistent with the user cost and firm level data used in the regressions, I divide the values in each series by 100, which creates a value of one in the base year (1990).

3.2.1 User Cost of Capital

To start, I follow the approach of Chirinko et al. (1999) in deriving the user cost of capital. Their methodology creates industry-specific user costs from a weighted average of asset user costs, with the weights determined by the proportion of capital accounted for by each asset within each industry. The actual data used in Chirinko et al. (1999) were proprietary to Data Resources, Inc. (DRI) and are no longer available. As a result, I follow Spatareanu (2008) and rely upon the data provided by the Bureau of Labor Statistics (BLS) to estimate industry level, capital service flows within the multifactor productivity framework; specifically, the data used in the estimation of the implicit rental price of capital. The data, which are available online from the BLS, includes detailed, asset-specific information for 63 types of capital assets utilized by manufacturing industries from 1987 to 2010.[15] This rich dataset contains many of the time-varying, asset-specific components of the user cost, namely: capital stocks, price deflators for new capital goods, tax incentive parameters, and depreciation rates.

Using the BLS data, Spatareanu (2008) constructed a user cost series for U.S. manufacturing industries in a similar manner to Chirinko et al. (1999). The data used in Spatareanu (2008) covered the period from 1982-2001, and included only 44 different capital assets. That earlier data is no longer available from the BLS. A full list of the 63 asset codes used in this study and their descriptions from the current BLS dataset are presented in Appendix 3.B.

Following Chirinko et al. (1999), the time-varying, industry-specific, user cost of capital, $U_{i,t}$, is defined as:

$$U_{i,t} = \sum_j w_{i,j,t} \left[\left(\frac{p_{j,t}}{p_{i,t}} \right) (r_t + \delta_{j,t}) \, \theta_{j,t} \right] \tag{3.6}$$

where $w_{i,j,t}$ is the weight of asset j in the total capital stock of industry i at time t, $p_{j,t}$ is the asset-specific price deflator for new capital goods, $p_{i,t}$ is the industry-specific price deflator for output, r_t is the financial cost of capital, $\delta_{j,t}$ is an asset-specific depreciation rate, and $\theta_{j,t}$ is an asset-specific tax parameter that takes into consideration investment tax incentives. Each of these components is described in greater detail below.

With this formulation, each industry-level user cost is derived as a time-varying, weighted average of the user costs for each capital asset. Each weight, $w_{i,j,t}$, is calculated as the percentage of the total productive stock of all capital assets (excluding inventory stocks) within each industry and for each time period, which is accounted for by the productive stock of each individual asset. The value for the productive stock of each asset within an industry for each time period is taken directly from the BLS dataset.[16] Each asset-specific user cost is defined by the more familiar terms found within the brackets of Equation (3.6).

The first term, $p_{j,t}/p_{i,t}$, measures the relative price of new capital goods to output. The price deflator for new capital goods is asset-specific with a base year of 2005 and is taken directly from

[15]The BLS lists additional capital assets, but only 63 are actually used by manufacturing industries during the available timeframe. The data can be found at http://www.bls.gov/mfp/mprdload.htm under "Rental Price Detail Measures by Asset Type" for manufacturing industries.

[16]The BLS dataset also provides values for the wealth stock of capital assets. The difference between the productive stock and wealth stock lies in the choice of the depreciation schedule used in the perpetual inventory method of estimation for the asset stocks used by the BLS. For this analysis, the productive stock is chosen as the most representative measure, because the age/efficiency schedules are based in part on empirical evidence of capital depreciation.

the BLS dataset. The BLS defines this variable as current dollar investment divided by constant (2005) investment, so this measure is a price deflator for the flow of new investment rather than for the existing stock of capital assets. The price deflator for output is industry-specific with a base-year of 2005 and is calculated from the chain-type price indexes for gross output by industry from the BEA.[17]

The second set of terms, within parentheses, represents the real, financial cost of capital including depreciation coverage. As in Chirinko et al. (1999), the financial cost of capital, r_t, is the same for all industries and assets, and it is defined as:

$$r_t = 0.67\,(div_t + 0.024) + 0.33\big((1-\tau_t)\,Aaa_t - \Pi_t\big) \tag{3.7}$$

where $(div_t + 0.024)$ is the dividend-price ratio for Standard and Poor's Composite Stock Price Index plus an expected long-run growth rate of 2.4%, and Aaa_t is the average annual yield on Moody's Aaa-rated corporate bonds. This rate is discounted by one minus the corporate tax rate, τ_t, to account for the deductibility of interest payments and then adjusted for inflation, Π_t. This formulation for r_t is essentially an approximation of the weighted average cost of capital for the U.S. economy as a whole. The source of the dividend-price ratio and the Aaa bond rate is the *Economic Report of the President, 2012* (ERP), Tables B-95/6 and B-73, respectively.[18] The corporate tax rate was obtained by contacting the multifactor productivity section of the BLS, since it is not reported in the capital asset dataset. The rate of inflation is calculated from the implicit price deflators for gross domestic product with a base year of 2005, as reported by the BEA in the National Income and Product Accounts (NIPA) Table 1.1.9. The asset-specific depreciation rate, $\delta_{j,t}$, is reported in the BLS data.

The final term in Equation (3.6) is the tax parameter, $\theta_{j,t}$, which accounts for the investment incentives associated with depreciation write-offs and investment tax credits. The value of the tax parameter is taken directly from the BLS dataset and is defined as

$$\theta_{j,t} = \frac{1 - \tau_t z_{j,t} - \phi_{j,t}}{1 - \tau_t} \tag{3.8}$$

[17] The data can be downloaded at `http://www.bea.gov/iTable/index_industry.cfm`.

[18] The data can be downloaded at `www.gpoaccess.gov/eop/download.html`.

where τ_t is the corporate income tax, $z_{j,t}$ is the present value of one dollar of tax depreciation allowances and $\phi_{j,t}$ is the effective rate of the investment tax credit.

Table 3.6. Summary Statistics of the Industry-specific User Cost and the Asset-specific Components of the User Cost

Year	User cost $U_{i,t}$		Relative price $p_{j,t}/p_{i,t}$		Real cost of capital $(r_t + \delta_{j,t})$		Tax parameter $\theta_{j,t}$	
	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
1987	0.1135	0.0288	5.2787	17.0640	0.1439	0.0945	1.2603	0.1499
1988	0.1140	0.0308	4.8043	15.2498	0.1548	0.0954	1.2051	0.1157
1989	0.1079	0.0273	4.3036	13.2050	0.1516	0.0945	1.1996	0.1159
1990	0.1100	0.0251	3.8090	10.7314	0.1538	0.0944	1.2004	0.1159
1991	0.1100	0.0264	3.4918	9.2838	0.1548	0.0986	1.1935	0.1160
1992	0.1108	0.0271	3.0899	7.3753	0.1549	0.0973	1.1853	0.1160
1993	0.1084	0.0274	2.6842	5.7640	0.1550	0.1008	1.1808	0.1237
1994	0.1140	0.0301	2.4136	4.8690	0.1623	0.1034	1.1978	0.1301
1995	0.1100	0.0280	2.0870	3.7161	0.1600	0.1038	1.1925	0.1300
1996	0.1083	0.0231	1.7685	2.4730	0.1585	0.1047	1.1894	0.1299
1997	0.1070	0.0229	1.5609	1.6997	0.1518	0.1028	1.1879	0.1299
1998	0.1102	0.0308	1.4301	1.2251	0.1548	0.1024	1.1769	0.1292
1999	0.1104	0.0245	1.2994	0.8023	0.1590	0.1056	1.1846	0.1297
2000	0.1076	0.0126	1.1958	0.5279	0.1600	0.1076	1.1930	0.1300
2001	0.1089	0.0129	1.1592	0.3827	0.1538	0.1007	1.1778	0.1339
2002	0.1130	0.0139	1.1343	0.3014	0.1597	0.1036	1.1541	0.1417
2003	0.1066	0.0097	1.0862	0.1923	0.1615	0.1082	1.1346	0.1436
2004	0.1006	0.0094	1.0365	0.1019	0.1605	0.1103	1.1298	0.1460
2005	0.0994	0.0110	1.0000	0.0000	0.1496	0.1036	1.1556	0.1267
2006	0.1015	0.0141	0.9763	0.0763	0.1506	0.1026	1.1616	0.1275
2007	0.1038	0.0172	0.9685	0.1262	0.1512	0.1018	1.1611	0.1274
2008	0.1106	0.0222	0.9403	0.1786	0.1560	0.0995	1.1623	0.1276
2009	0.1204	0.0211	0.9709	0.1912	0.1641	0.1044	1.1569	0.1268
2010	0.1093	0.0225	0.9296	0.2050	0.1579	0.1027	1.1503	0.1258
N	20		887		887		887	

Summary statistics for the *industry-specific* user cost, which is calculated with time-varying weights according to Equation (3.6), and the three, major *asset-specific* components of it are presented in Table 3.6. The mean and standard deviation of the industry-specific user cost are remarkably stable over the entire timeframe of the sample. This result is unexpected given the large decline in both the mean and standard deviation of relative prices and the relative stability of both the mean and standard deviation of the other two components. In addition, the result is in conflict with the findings of Spatareanu (2008), which notes a steady decline in the user cost. In that study, the annual mean of the industry-level user cost decreases by 37% from 1987 to 2001, whereas I find a decrease of only 4% over the same time period. Given that the largest source of variation in the user cost is the variation in the relative price of capital, I investigate the relative price further by creating three alternative, relative price indexes that rely on weighted averages and compare them to the simple, unweighted mean of the asset-specific relative price of capital.

The first index is referred to as the relative price of capital index (RPK). The RPK is an annual, weighted average of the asset-specific relative prices with time-varying asset and industry weights. The RPK is defined as

$$RPK_t = \sum_i \mu_{i,t} \sum_j w_{i,j,t} \left(\frac{p_{j,t}}{p_{i,t}} \right) \tag{3.9}$$

where $\mu_{i,t}$ is the weight of the capital stock of industry i in the total capital stock of all U.S. manufacturing industries at time t, $w_{i,j,t}$ is the weight of asset j in the total capital stock of industry i at time t, and $p_{j,t}/p_{i,t}$ is the asset-specific relative price of new capital goods to industry output. The second and third indexes are referred to as fixed-weight relative price of capital indexes (RPKF). Each RPKF is an annual, weighted average of the asset-specific relative prices with fixed asset weights and time-varying industry weights. I create two RPKF indexes: one with a base year of 1999, which falls in the middle of the sample period, and one with a base year of 2005, which is the base year for the asset and output deflators. Each RPKF is defined as

$$RPKF_t^{BY} = \sum_i \mu_{i,t} \sum_j w_{i,j,BY} \left(\frac{p_{j,t}}{p_{i,t}} \right) \tag{3.10}$$

where $\mu_{i,t}$ is the weight of the capital stock of industry i in the total capital stock of all U.S. manufacturing industries at time t, $w_{i,j,BY}$ is the weight of asset j in the total capital stock of industry i in the chosen base year, and $p_{j,t}/p_{i,t}$ is the time-varying, asset-specific relative price of new capital goods to industry output.

In Figure 3.3, I compare time series plots for the simple mean (unweighted average) of relative prices of capital for all capital assets, computer and system hardware or software, machinery and equipment, and structures and other capital assets.[19] As was shown in the summary statistics, the mean of the relative price for all capital assets declines steadily over the sample. The relative price means for machinery and equipment and for structures and other assets are relatively flat, while the mean for computer and system hardware or software falls dramatically. It is clear from Figure 3.3

[19]Computer and system hardware or software include asset codes 32-42, machinery and equipment include asset codes 2-30, and stuctures and other capital assets include asset codes 43-95. The asset codes and their descriptions are listed in the Appendix

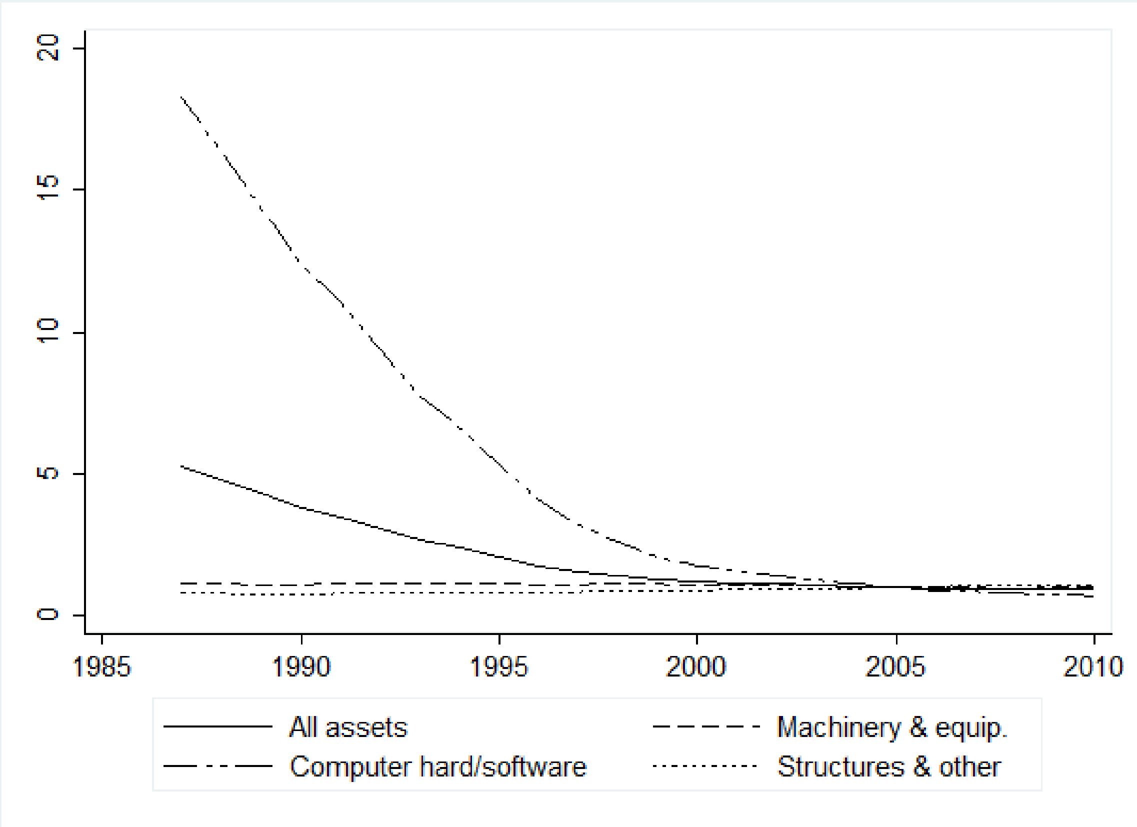

Figure 3.3. Unweigted Averages of the Relative Price of Capital by Type of Asset, 1987-2010

that the decline for all assets is driven largely by the decline in the relative price of computer-based capital assets to industry output over this time period.

In Figure 3.4, I compare time series plots for the alternative price of capital indexes, which are based on weighted averages for all assets. In contrast to the unweighted average of the relative price for all assets, the time-varying weighted average of the relative price of capital, as measured by the RPK, actually tends to increase from 1987-2001. After 2001, the trajectory of the RPK tends to be relatively flat. The RPKF with 2005 fixed asset weights, on the other hand, follows the downward trajectory of the simple mean until 1997, afterwhich it closely mirrors the path of the RPK. The RPKF with year 1999 fixed asset weights declines much less dramatically than the 2005-based RPKF from 1987 to 1997, before mirroring the RPK.[20]

---

[20] Although not reported, I also created indexes that equally weight the capital stock of each industry as a portion of the capital stock of all U.S. manufacturing industries, as a whole. In other words, I replace $\sum \mu_{i,t}$ in Equation (3.10) with $1/n \sum_{i}$. The overall results were largely unchanged.

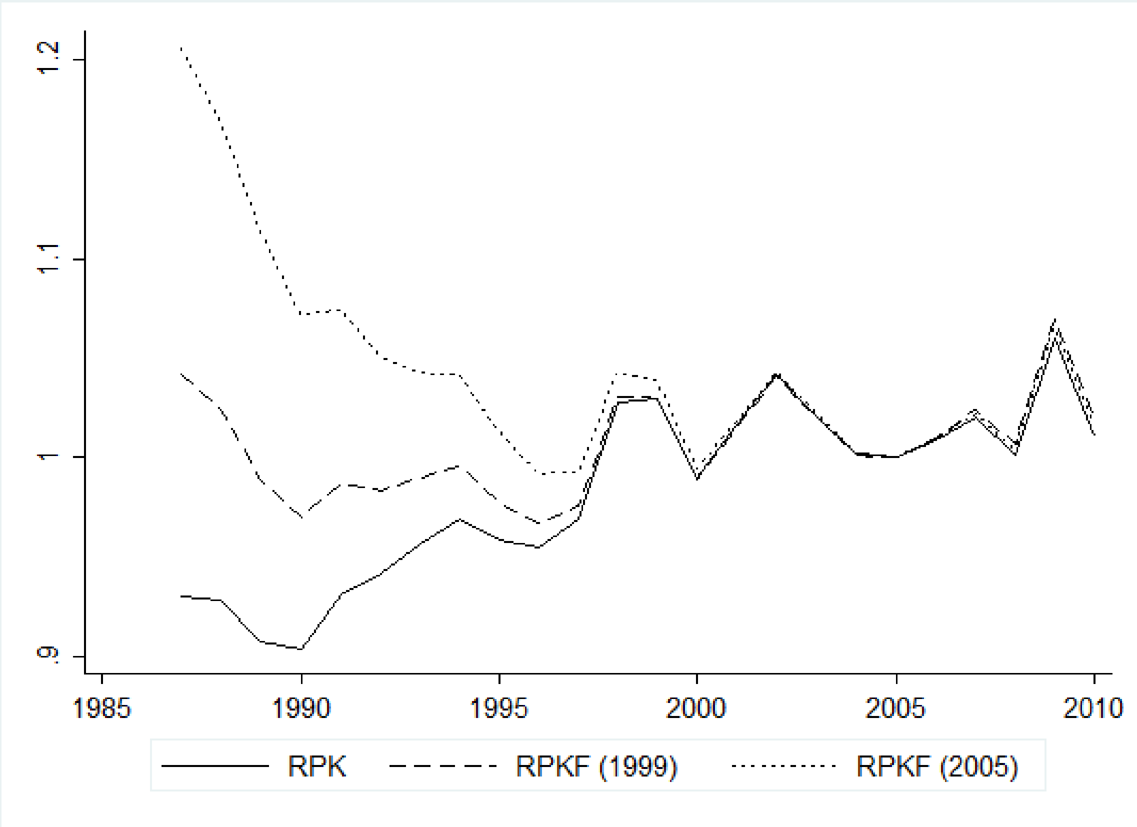

Figure 3.4. Weighted Averages of the Relative Price of Capital for All Assets, 1987-2010

Two important points arise from these findings. First, in periods of substantial economic change (in this case rapidly declining prices of computer-based capital assets), different weighting schemes can lead to drastically different conclusions regarding the behavior of the relative price of capital assets to output for manufacturing industries. Taken together, the declining unweighted average of the relative price and the slightly rising time-varying weighted RPK suggests that weights are shifting in such a way that the capital assets with rising relative prices are getting increased weights over time. In other words, the weights are rising for assets whose relative prices are increasing and falling for assets whose relative prices are decreasing. Because the weights are *shares* of the assets in the total capital expenditures of each industry, these results suggest that the demand for capital assets is relatively price-inelastic. With an elasticity of demand that is less than one, a rise in quantity will be proportionally smaller than a fall in price. As a result, industry expenditure on capital goods will decrease and the share of those assets in total capital expenditures will also decrease. By using time-varying weights, the capital assets with a falling price have shrinking shares; thus, they are not given enough importance in the construction of the weighted average user cost.

Second, even with fixed weights, the behavior of the relative price indexes are highly sensitive to the arbitrary choice of the base year. In the case of fixed weights, as one moves farther away from the base year, the assets with falling prices are given too much importance in the construction of a weighted average. Both of these points are addressed explicitly in Landefeld and Parker (1997), Steindel (1995), and Triplett (1992), among many others, as primary motives for using chain-weighting procedures in the construction of aggregated economic time series.

In order to test the sensitivity of my results to the choice of weighting scheme, I therefore create three alternative user cost series. The first two series use fixed asset weights, with base years of 1999 and 2005, to create a fixed-weight user cost (UF). The formula for the UF is

$$UF_{i,t}^{BY} = \sum_j w_{i,j,BY} \left[\left(\frac{p_{j,t}}{p_{i,t}} \right) (r_t + \delta_{j,t}) \, \theta_{j,t} \right] \tag{3.11}$$

where $w_{i,j,BY}$ is the weight of asset j in the total capital stock of industry i for the selected base year, BY. For the third series, I create a chain-weighted user cost index, which essentially compares adjacent years with alternative base years (the current year and preceding year), takes a geometric average of the implied growth rates, and uses those growth rates to construct the chained user cost index.

The construction of the chain-weighted user cost index can be described in three steps. First, for every pair of years t and $t-1$, I calculate a user cost, u, using year t weights:

$$\begin{aligned} u_{i,t}^{t} &= \sum_j w_{i,j,t} \left[\left(\frac{p_{j,t}}{p_{i,t}} \right) (r_t + \delta_{j,t}) \, \theta_{j,t} \right] \\ u_{i,t-1}^{t} &= \sum_j w_{i,j,t} \left[\left(\frac{p_{j,t-1}}{p_{i,t-1}} \right) (r_{t-1} + \delta_{j,t-1}) \, \theta_{j,t-1} \right] \end{aligned} \tag{3.12}$$

where superscript t on u indicates the year of the weights. Then, I calculate user costs for the same pair of years using $t-1$ weights:

$$\begin{aligned} u_{i,t}^{t-1} &= \sum_j w_{i,j,t-1} \left[\left(\frac{p_{j,t}}{p_{i,t}} \right) (r_t + \delta_{j,t}) \, \theta_{j,t} \right] \\ u_{i,t-1}^{t-1} &= \sum_j w_{i,j,t-1} \left[\left(\frac{p_{j,t-1}}{p_{i,t-1}} \right) (r_{t-1} + \delta_{j,t-1}) \, \theta_{j,t-1} \right]. \end{aligned} \tag{3.13}$$

Second, I take the geometric average of the growth factors calculated using each base year (t and $t-1$) to get one plus the geometric average rate of change of the user cost for industry i in year t:

$$1 + g_{i,t} = \sqrt{\left(\frac{u_{i,t}^{t}}{u_{i,t-1}^{t}}\right)\left(\frac{u_{i,t}^{t-1}}{u_{i,t-1}^{t-1}}\right)} \tag{3.14}$$

where the ratios in parentheses are equal to one plus the rate of increase in the user cost in year t, for the two, adjacent base years.

Lastly, I use these average rates of change to create the chained user cost index (UC). Because the price data are already indexed to 2005, I choose that year as the starting point for the chaining algorithm:

$$\begin{aligned}
&\ldots \\
&UC_{i,03} = UC_{i,04}/(1 + g_{i,04}) \\
&UC_{i,04} = UC_{i,05}/(1 + g_{i,05}) = 1.0/(1 + g_{i,05}) \\
&UC_{i,05} = 1.0 \\
&UC_{i,06} = UC_{i,05} * (1 + g_{i,06}) = 1.0 * (1 + g_{i,06}) \\
&UC_{i,07} = UC_{i,06} * (1 + g_{i,07}) \\
&\ldots
\end{aligned} \tag{3.15}$$

where $UC_{i,t}$ is the industry-specific, chain-weighted user cost index.

3.2.2 Firm Data: Investment and Capital Stocks

The industry-specific user cost data are joined with firm level data from Standard and Poor's Compustat annual, full coverage files based upon two-digit SIC codes. The firm level data are selected for the years 1987-2010 to match the user cost data and include those firms identified with manufacturing by their primary SIC (codes 2000-3999). I do want to note that merging the user cost and firm data is imperfect due to the timing convention in Compustat. The user cost data is based upon a calendar year (January-December), while the Compustat data is based upon fiscal year, which can vary from firm to firm. The convention used in Compustat is to assign the data from firms with a fiscal year end in January-May to the previous calendar year. Those firms with a fiscal year end in June-December are assigned to the current calendar year. This convention attempts to align the firms data with the year in which the majority of its operations took place.[21]

[21] Chirinko et al. (1999) avoid this predicament by using quarterly user cost data from DRI and finding annual averages that correspond to each firm's fiscal period. As noted previously, that data is unavailable.

The dependent variable used for estimation is real firm investment scaled by the previous period's real capital stock, $I_t/\hat{K}_{t-1}$ (firm subscripts are suppressed for simplicity). The nominal measure of investment is the value of the firm's capital expenditures for the year, t, as reported in the firm's statement of cash flows and downloaded from Compustat.[22] Nominal investment is converted to real values using the appropriate capital price index, as determined by which measure of the user cost is included in the regressions. In other words, if I include the time-varying weighted user cost in the regression, I deflate nominal investment with a time-varying weighted capital price index. If I include the chain-type user cost, I deflate investment with a chain-type capital price index, and so on. As a result, I construct four separate capital price indexes to match the four different measures of the user cost. Each index is constructed in the same manner as described in the user cost section above. These capital price indexes are industry-specific, so they are joined with the firm data based upon two-digit SIC codes. The real capital stock at the end of the previous reporting period, $\hat{K}_{t-1}$, is the lagged, real value of the estimated replacement value of property, plant and equipment. The nominal value of the replacement cost of capital is deflated in the same manner as nominal investment.

Because using book values of gross or net property, plant and equipment can understate the current value of capital, I follow Chirinko et al. (1999) in deriving a nominal replacement value of capital series for each firm. The underestimation associated with book values is particularly pronounced if capital is many years old or during periods of high inflation. In constructing the replacement cost of capital series, I rely upon the algorithm used by Chirinko et al. (1999), which is described in an unpublished appendix made available by the authors.

The algorithm works by iteratively building a replacement value series using three steps. First, inflate the previous year's value by aggregate inflation to obtain the current year value in the absence of other changes. Then, add the value of the current year change in the capital stock. Last, account for capital lost to depreciation. The main formula for the iterative algorithm is

$$\hat{K}_t = \left[\hat{K}_{t-1}\left(\frac{P_t}{P_{t-1}}\right) + \Delta K_t\right](1-\delta) \tag{3.16}$$

where $\hat{K}_t$ is the replacement value of the capital stock at time t, P_t is the implicit price deflator for non-residential capital goods, ΔK_t is a capital change variable, and δ is a capital goods depreciation rate. Each of these variables is described in greater detail below.

[22] The Compustat code for capital expenditures is *capx*.

To set the seed value for the firm's initial capital stock, I use the reported book value of net property, plant and equipment for the first observation of each firm available in Compustat.[23] The data for Compustat goes back as far as 1950, and the earliest reported book value is the closest available value to the cost of new capital for the firm at that time. The initial book value from Compustat will usually be less than the corresponding replacement cost, but any distortionary effect will decline as the initial capital depreciates. The price deflator for non-residential capital goods is obtained from NIPA Table 5.3.4, Chain-Type Price Indexes for Private Fixed Investment by Type.[24]

Following Chirinko et al. (1999), the derivation of the capital change variable, ΔK_t relies upon the following accounting identities

$$\Delta PPEGT_t = I_t + ACQ_t - RET_t \tag{3.17}$$

$$\Delta PPENT_t = I_t + ACQ_t - DEPR_t \tag{3.18}$$

where $\Delta PPEGT_t$ is the change in gross property, plant and equipment from year $t-1$ to year t, $\Delta PPENT_t$ is the change in net property, plant and equipment from year $t-1$ to year t, ACQ_t is an increase in capital due to a merger or acquisition, RET_t is a decrease in the capital stock due to the retirement of obsolete or damaged capital assets, and $DEPR_t$ is book depreciation.

In the event of an acquisition, the capital change variable is the sum of current period investment and the increase in capital from the acquisition. Because Compustat does not have reliable figures for ACQ_t, I rearrange Equation (3.17) to determine the change in capital

$$\Delta K_t = \Delta PPEGT_t + RET_t \tag{3.19}$$

In the event of a divestiture, however, the capital stock should be decreased by the depreciated value of the capital sold, which by Equation (3.18), implies

$$\Delta K_t = \Delta PPENT_t \tag{3.20}$$

[23]The Compustat code for net property, plant and equipment is *ppent*.

[24]The data can be downloaded at `http://www.bea.gov`.

If there is no major acquisition or divestiture, then the capital change is simply equal to the current year's investment

$$\Delta K_t = I_t \tag{3.21}$$

To determine whether a firm has undergone an acquisition or divestiture in a given year, I use the rules of thumb devised by Chirinko et al. (1999). The first rule relies upon the assertion that $\Delta PPEGT_t$ is normally less than I_t due to retirements. Therefore, if $\Delta PPEGT_t > I_t$ by a substantial amount, it signals an acquisition with a high probability. The second rule relies upon the assertion that $\Delta PPEGT_t$ is normally greater than RET_t, because apart from a divestiture, retirements are the only way to reduce $PPEGT_t$. Therefore, if $\Delta PPEGT_t < RET_t$ by a substantial amount, it signals a divestiture.[25]

Chirinko et al. (1999) define a substantial amount as ten percent or more, which creates three distinct rules for the capital change variable that can be determined from available Compustat data. If rule one holds,

$$\frac{\Delta PPEGT_t - I_t}{PPEGT_{t-1}} > 0.1 \tag{3.22}$$

and I assume an acquisition. I then use Equation (3.19) to determine the capital change. If rule two holds,

$$\frac{\Delta PPEGT_t + RET_t}{PPEGT_{t-1}} < -0.1 \tag{3.23}$$

and I assume a divestiture. I then use Equation (3.20) to determine the capital change. If neither rule holds, the capital change is equal to investment as in Equation (3.21).

The final part of the algorithm is the rate of capital depreciation, δ. Chirinko et al. (1999) start with three initial assumptions. First, all of a firm's capital has the same life. Second, firms use a straight-line depreciation method for book depreciation. Third, all investments are made at the beginning of the year, and all depreciation is taken at the end of the year. Given these assumptions,

$$LIFE_t = \frac{PPEGT_{t-1} + I_t}{DEPR_t} \tag{3.24}$$

where $LIFE_t$ is the useful capital stock life in year t. Because $LIFE_t$ is time-varying, the average life for each firm over the sample, $\overline{LIFE}$, is used to determine the depreciation rate. Following Chirinko et al. (1999), the estimated, average capital goods depreciation rate used in the replacement

[25] The Compustat code for gross property, plant and equipment is *ppegt*. For retirements, it is *ppevr*.

cost algorithm is $\delta = 1.5/\overline{LIFE}$. This choice of depreciation rate represents a conservative estimate of depreciation that falls between a double declining and a single declining balance, and prevents one from devaluing the capital stock too quickly.

Even with this conservative estimate for the average depreciation rate, the capital stock is sometimes devalued too quickly. This situation arises when a firm's reported depreciation is inconsistent with its $PPEGT$ and $PPENT$ figures. To identify this scenario, I compare the estimated replacement cost (using the firm's reported book depreciation), $\hat{K}$, to the book value of $PPENT$ in the final year of data (T) for each firm. In an inflationary environment, one would expect $PPENT_T$ to be less than the replacement cost of capital, $\hat{K}_T$. If this is the case, then I use the book value of depreciation reported by the firm in Equation (3.24). On the other hand, if $PPENT_T > \hat{K}_T$, then the imputed depreciation rate is probably too large. If this is the case, I formulate an alternate measure of depreciation by subtracting Equation (3.18) from Equation (3.17) and rearranging to obtain

$$DEPR_t^a = \Delta PPEGT_t - \Delta PPENT_t + RET_t \tag{3.25}$$

where $DEPR_t^a$ is the alternate measure of depreciation to be used in Equation (3.24). I then create an alternate replacement cost of capital series, $\hat{K}_t^a$ using the alternate depreciation rate. If $\hat{K}_T^a > \hat{K}_T$, I use the alternate series for the replacement cost. Otherwise, I use the original formulation.

3.2.3 Other Firm Level Data

In addition to the percentage change in the user cost, I include as independent variables a sales variable to capture accelerator effects and a cash flow variable to capture liquidity constraints. Because the accelerator affects the desired capital stock, it is included in the regressions as the percentage change in the real value of firm level sales, $\Delta S_t/S_{t-1}$. The nominal value is net sales as reported on the firm's income statement and downloaded from Compustat.[26] This value is then deflated by the industry-specific output price deflator used to define the user cost in Equation (3.6).

In order to capture the effect of liquidity constraints, the cash flow variable, $CF_t/\hat{K}_{t-1}$, enters the regression in levels. It is scaled by the real, replacement value of capital, which is also used to scale investment. Cash flow is measured as the sum of income before extraordinary items;

[26] Compustat defines net sales as gross sales reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers. The Compustat code for net sales is *sale*.

depreciation and amortization; deferred taxes; equity in net loss (earnings); and extraordinary items and discontinued operations.[27] All of these components are taken from the firm's statement of cash flows and downloaded from Compustat.[28] The first two components (income and depreciation) are seldom missing from the firm's statement of cash flows. If a firm reports a missing value for either, I produce a missing value for cash flow. The last three items, however, are less commonly reported. If these components are missing in Compustat, I assume that their values are economically insignificant, and I set them to zero.

Following Chirinko et al. (1999) and Spatareanu (2008), I exclude observations in the 1% upper and lower tails of the firm-level sales growth and cash flow to capital stock variables to protect against the results being driven by a small number of extreme observations. To avoid a censured regression bias, I do not eliminate outliers from the firm-level, independent variable $(I_t/\hat{K}_{t-1})$. I also do not trim the tails of the user cost variable distribution, because the user cost is derived from more stable aggregate and industry-level data. After creating the firm level regression variables, deleting observations with missing values and trimming outliers, the sample contains 3,864 firms with 42,749 observations from 1989-2010. The panel is unbalanced due to firm-specific entry and exit and contains gaps due to the deletion of outliers.

3.2.4 Unit Root Tests

For a number of reasons, the choice of which stationarity tests to perform on the variables in the firm level dataset is not as straightforward as it was in the industry level section. First, the sample has dimensions of $N = 3,864$ and $T = 22$, which suggests that the test chosen should have asymptotic requirements of $N \to \infty$ in order to ensure consistency in the test statistics. The panel, however, is unbalanced and has gaps in the time series component. The Fisher-type test, as outlined in Choi (2001), is the only panel data unit root test that can handle panels with gaps in the data; however, the asymptotic requirements for this test are $T \to \infty$. For the firm level regressions, investment and cash flow are scaled by capital, and the user cost and sales variables are measured in growth rates; therefore, I have little *a priori* reason to expect the presence of a unit root in these data.

---

[27] Given my sample period of 1987-2010, cash flow from operations, as reported in the firm's Statement of Cash Flows, may be a superior measure of cash flow. I choose the aforementioned measure of cash flow for comparability to previous investment studies.

[28] The Compustat codes are ibc, *dpc*, *txdc*, *esubc*, and *xidoc*, respectively

The exchange rate variables, on the other hand, present a peculiar problem. As was demonstrated in the industry level analysis, the exchange rate, as measured by the real, broad index of the value of the U.S. dollar, displayed evidence of a purely time series unit root when measured in log levels and log differences. The three industry-specific exchange rate series showed no evidence of panel nonstationarity when measured in log differences. The problem faced in the firm level analysis is that it is an empirical question as to whether the exchange rate variable should enter in level or difference form.

Because the Fisher-type test is imperfect for the full firm-level dataset, I separate out the different exchange rate variables and perform either time series or panel data unit root tests on these variables in a more appropriate setting. This decision creates an additional problem concerning the unit root tests for the industry-specific exchange rates. The time dimension for the data used in the firm analysis is only 22 years. As noted in the industry level section, the LLC test is the panel unit root test recommended for moderate size panels with a minimum of $T = 25$. To my knowledge, there are no panel unit root tests that are recommended when $T < 25$. As a result, I use the full set of data available for the exchange rates (1974-2010) to test for unit roots.

In the upper section of Table 3.7, I present the results for the time series unit root tests for the exchange rate. The PP test is performed on both the exchange rate and the natural log of the exchange rate in levels and differences. Also, the tests are performed with and without a trend. Both the exchange rate and the log of the exchange rate show evidence of nonstationarity when measured in levels. When measured in differences, however, both variables show evidence that the unit root is removed. My preference is to enter the exchange rate into the regressions without a log transformation, because the user cost and firm level variables are not measured as such. These results suggest that the log transformation has no effect on the presence of a unit root by itself. Rather, differencing the data is the necessary transformation to achieve stationarity. As a result, any regressions including the level of the real exchange rate series will be treated with extreme caution.

In the lower section of Table 3.7, I present the results for the panel unit root tests for the industry-specific exchange rates. As noted above, I prefer to include the exchange rate variables without a log transformation, so I present the tests for each industry-specific exchange rate measured in levels and differences. The panel test chosen is the LLC test, which is performed on the actual data and demeaned data and with or without a trend. These results suggest that even without the

Table 3.7. Exchange Rate Series Unit Root Tests, 1974-2010

Phillips-Perron time series data test						
H_o: Variable contains a unit root. H_a: Variable is stationary.						
		Levels			Differences	
Variable	Trend	Z_t	p-value[a]	Trend	Z_t	p-value[a]
e_t	No	-2.125	0.2347	No	-3.688	0.0043
	Yes	-2.102	0.5450	Yes	-3.658	0.0253
$\ln e_t$	No	-2.094	0.2470	No	-3.651	0.0049
	Yes	-2.068	0.5637	Yes	-3.621	0.0281

Levin-Lin-Chu panel data test[b]($N = 20$, $T = 40$)						
H_o: Panels contain unit roots. H_a: Panels are stationary.						
		Actual Data			Demeaned Data	
Variable	Trend	Adj. t*	p-value	Trend	Adj. t*	p-value
ter_t^i	No	-5.6626	0.0000	No	-4.4428	0.0000
	Yes	-2.5516	0.0054	Yes	-3.7479	0.0001
Δter_t^i	No	-11.7150	0.0000	No	-17.6606	0.0000
	Yes	-9.7950	0.0000	Yes	-14.2804	0.0000
xer_t^i	No	-6.0270	0.0000	No	-6.0803	0.0000
	Yes	-3.2664	0.0005	Yes	-5.7142	0.0000
Δxer_t^i	No	-12.1570	0.0000	No	-14.9517	0.0000
	Yes	-10.1797	0.0000	Yes	-12.0719	0.0000
mer_t^i	No	-5.1452	0.0000	No	-5.9577	0.0000
	Yes	-3.1681	0.0008	Yes	-2.3710	0.0089
Δmer_t^i	No	-12.6379	0.0000	No	-16.5525	0.0000
	Yes	-10.6083	0.0000	Yes	-13.8653	0.0000

[a] MacKinnon approximate p-values. Three Newey-West lags used in calculating the standard errors, as determined by the plug-in estimator, $4(T/100)^{2/9}$.
[b] The number of lags for each panel is chosen by minimizing AIC criteria, and the asymptotics for each test require $N/T \to \infty$.

log transformation, the industry-specific exchange rates show no evidence of nonstationarity when measured in levels or differences.

Although imperfect, I perform the Fisher-type panel unit root tests on the remaining variables in the sample, due to the presence of gaps in the data. In Table 3.8, I present the results of the tests for the investment, user cost and cash flow variables that are measured using the chain-type weighting system.[29] Also included are the results for the sales accelerator variable, which is unaffected by any particular weighting scheme. The Fisher-type test combines the results from

[29] Although not reported, the tests for the variables using time-varying weights and fixed-weights yield similar results

individual panel PP tests into three statistics. The tests are run on the actual data and demeaned data and with or without a trend. The results presented in Table 3.8 find no evidence for the presence of unit roots in the panel for the firm level data and user cost.

Table 3.8. Fisher-type Panel Data Unit Root Tests,[a] 1989-2010

H_o: All panels contain a unit root. H_a: At least one panel is stationary.

Variable	Trend	Actual Data Statistic[b]		p-value	Trend	Demeaned Data Statistic[b]		p-value
$I_t/\hat{K}_{t-1}$	No	Z	-100.4680	0.0000	No	Z	-98.9469	0.0000
	No	L^*	-163.9896	0.0000	No	L^*	-161.8957	0.0000
	No	P_m	254.3478	0.0000	No	P_m	252.5011	0.0000
	Yes	Z	-90.7769	0.0000	Yes	Z	-88.8686	0.0000
	Yes	L^*	-155.4245	0.0000	Yes	L^*	-152.9383	0.0000
	Yes	P_m	235.7655	0.0000	Yes	P_m	234.0529	0.0000
$\Delta UC_t/UC_{t-1}$	No	Z	-141.8497	0.0000	No	Z	-94.2812	0.0000
	No	L^*	-224.4693	0.0000	No	L^*	-133.8389	0.0000
	No	P_m	353.1715	0.0000	No	P_m	200.7643	0.0000
	Yes	Z	-119.4268	0.0000	Yes	Z	-93.9765	0.0000
	Yes	L^*	-201.9933	0.0000	Yes	L^*	-142.3658	0.0000
	Yes	P_m	312.4861	0.0000	Yes	P_m	214.3693	0.0000
$\Delta S_t/S_{t-1}$	No	Z	-119.2912	0.0000	No	Z	-117.9514	0.0000
	No	L^*	-177.1570	0.0000	No	L^*	-174.6767	0.0000
	No	P_m	271.6570	0.0000	No	P_m	268.4236	0.0000
	Yes	Z	-109.7911	0.0000	Yes	Z	-107.3203	0.0000
	Yes	L^*	-171.5955	0.0000	Yes	L^*	-166.2029	0.0000
	Yes	P_m	257.9479	0.0000	Yes	P_m	248.8267	0.0000
$CF_t/\hat{K}_{t-1}$	No	Z	-60.1255	0.0000	No	Z_t	-39.2658	0.0000
	No	L^*	-89.6461	0.0000	No	L_t^*	-63.1043	0.0000
	No	P_m	140.0062	0.0000	No	P_m	102.6998	0.0000
	Yes	Z	-64.2845	0.0000	Yes	Z_t	-47.7151	0.0000
	Yes	L^*	-104.3474	0.0000	Yes	L_t^*	-81.9070	0.0000
	Yes	P_m	156.7252	0.0000	Yes	P_m	126.7537	0.0000

[a] Based on Phillips-Perron tests with two Newey-West lags. The asymptotics assume $T \to \infty$.
[b] The Z, L^*, and P_m tests are based on the inverse standard normal, the inverse logit, and the modified inverse χ^2 distributions, respectively.

3.A Concordance for 2002 I-O Codes to 1987 SIC Codes

In this appendix, I describe the methodology used to create the concordance between 2002 Benchmark I-O Codes (6-digit) to 1987 SIC codes (2-digit). I start with the BEA's concordance between the 2002 Benchmark I-O codes and 2002 NAICS codes as published in Appendix A of the *Survey of Current Business* by Stewart et al. (2007). This concordance links the 6-digit I-O codes of the use table to 2002 NAICS codes which range from the 3-digit to the 6-digit level. I then use the 2002 NAICS to 1987 SIC concordance published by the US Census Bureau.[30] Of the 279 6-digit I-O codes that are classified as "Manufacturing Industries" in the benchmark accounts, 22 do not have a direct link to a single 2-digit 1987 SIC code. For these 22 industries, the 6-digit I-O code is related to a 2002 NAICS code which, in turn, is related to two or more 2-digit 1987 SIC codes. In order to estimate which portion of the I-O use table value should be attributed to each 2-digit 1987 SIC code, I use the concordance between 2002 NAICS and 1987 SIC codes that is used by the BLS in their construction of the PPI.[31] With the BLS concordance, I can investigate the link between the 2002 NAICS and 1987 SIC at a more detailed level of disaggregation than that of the Census concordance. I then make the assumption that these very detailed industries use inputs in the same proportion as the output of each industry within a particular NAICS code. I use value of shipments data from the 2002 Economic Census to determine the proportion of output for each industry in question.[32]

Table 3.9. Example of Concordance between 6-digit, 2002 I-O Code and 2-digit, 1987 SIC Code

2002 I-O code	2002 NAICS code	1987 SIC code	Shipments ($1,000)	Portion of output
BEA and Census concordances:				
326110	32611	26 and 30		
BEA and BLS concordances:				
326110	32611		28,185,043	100%
	326113	30	14,287,644	51%

In Table 3.9, I present an example of how I determine the distribution of 2002 IO code 326110, Plastics packaging materials and unlaminated film and sheet manufacturing. The BEA concordance links 2002 I-O code 326110 to 2002 NAICS code 32611. The Census concordance links 2002 NAICS code 32611 to 1987 SIC codes 26 and 30. The BLS concordance links 2002 NAICS code 326113 to 1987 SIC code 30. Using the shipments data from the 2002 Economic census, I determine that 51% of the ouput from NAICS code 32611 can be attributed to industry 326113. I, therefore, attribute 51% of the use table values for I-O code 326110 to SIC code 30 and the remaining 49% to SIC code

[30] The concordance can be downloaded at `http://www.census.gov/eos/www/naics/concordances/concordances.html`.

[31] The concordance can be found at `http://www.bls.gov/ppi/ppinaics.htm`.

[32] The data can be found at `http://factfinder2.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t`.

26. Using this same methodology, I can parcel out the remaining 21 NAICS codes that do not have a direct link to a single 2-digit 1987 SIC code.

Working backwards from the Census concordance between 1987 SIC and 2002 NAICS codes, and then again from the BEA concordance between 2002 NAICS and 2002 I-O codes, I determine that there are eleven 6-digit I-O codes that are classified as "Non-manufacturing" industries, but would have been considered "Manufacturing" in the 1987 SIC scheme. These industries should also be included in the updated manufacturing technology matrix, since it is constructed for the 2-digit 1987 SIC classification system. Of these eleven industries, six have a direct link between 6-digit I-O and 2-digit 1987 SIC codes. Of the remaining five, three can be parceled out using the methodology explained above. I choose to ignore the last two I-O codes for lack of additional information, and I do not include them in the construction of the updated technology matrix. One of the I-O codes is 48A000, Scenic and sightseeing transportation and support activities. Some part of it is related to SIC 3731, Repair services provided by floating dry docks, but I am unable to clearly delineate sales data for that SIC code. The other I-O code is 1119B0, All other crop farming. Some part of it is realted to SIC 2099, but I cannot find a link deeper than NAICS code 111998, which is related to SIC codes 2099, 0191, 0831 and 0919. I, therefore, cannot use the proportion of sales method, as used in other cases.

3.B Asset Codes

Table 3.10: Capital Assets Used in U.S. Manufacturing Industries

Asset code	Asset description
Non-residential Equipment	
2	Other Furniture
3	Other Fabricated Metal Products
4	Steam Engines and Turbines
5	Internal Combustion Engines
6	Farm Tractors
7	Construction Tractors
9	Construction Machinery, excluding tractors
10	Mining and Oilfield Machinery
11	Metalworking Machinery
12	Special Industry Machinery, n.e.c.
13	General Industrial Equipment incl. Materials Handling
14	Office and Accounting Machinery
15	Service Industry Machinery
16	Communications Equipment
17	Electrical Transmission, Distribution, and Industrial Apparatus

Continued on Next Page…

Table 3.10 – Continued

Asset code	Asset description
18	Household Appliances
19	Other Electrical Equipment
20	Light Trucks, including SUVs
21	Other Trucks, Buses, and Truck Trailers
22	Autos
23	Aircraft
24	Ships and Boats
25	Railroad Equipment
26	Instruments: Photocopying and Related Equipment
27	Medical Equipment and Related Equipment
28	Electromedical Instruments
29	Nonmedical Instruments
30	Other Nonresidential Equipment
32	Mainframe Computers
33	Personal Computers (PCs)
34	Direct Access Storage Devices
35	Printers
36	Terminals
37	Tape Drives
38	Storage Devices
39	Integrated Systems
40	Software, pre-packaged
41	Software, custom
42	Software, own-account
Non-residential structures	
43	Industrial Buildings
44	Office Buildings
45	Commercial Warehouses
46	Other Commercial Buildings
47	Educational Buildings
49	Hotels and Motels
51	All Other Nonfarm Buildings
53	Telecommunications
54	Electric, Light, and Power
55	Gas
57	Petroleum Pipelines
58	Farm
59	Mining: Petroleum and Natural Gas
60	Other Mining
61	Other Nonresidential Structures
Other Capital Assets	
81	Land
83	Multimerchandise Shopping
84	Food and Beverage Establishments
86	Mobile Offices
87	Other Transportation
88	Other Land Transportation
89	Water Supply
90	Sewage and Waste Disposal

Continued on Next Page…

Table 3.10 – Continued

Asset code	Asset description
95	Highway and Conservation and Development

CHAPTER 4

INDUSTRY LEVEL ESTIMATES

This chapter is divided into two empirical sections: one on replication of previous work and one on my extension to the current body of literature. In the replication section, I summarize my attempts to reproduce the findings of Campa and Goldberg (1999), which is referred to in this chapter as the "benchmark" study for the industry-level estimates. In these efforts, I discover that the authors may have placed priority on the wrong set of violations to the assumptions necessary for classical least squares. I then extend their analysis using the updated dataset described in section 3.1.2 above. I investigate the sensitivity of the benchmark results to choices in the interest rate and the exchange rate variables. I also compare econometric techniques that address heteroskedasticity and cross-sectional dependence, which were likely ignored by Campa and Goldberg. Furthermore, I alter the investigation to determine the role that competition with imported final goods may have on investment, and I use industry-specific exchange rates to determine the net effect of the exchange rate on investment.

4.1 Replication

Campa and Goldberg (1999) used a three-stage least squares (3SLS) procedure on the following system of equations:

$$\begin{aligned}\Delta I_t^i &= \beta^i + \left(\beta_1 + \beta_2\chi_{t-1}^i + \beta_3\alpha_{t-1}^i\right)\left(\tilde{\kappa}_{t-1}^i\right)^{-1}\Delta\hat{e}_{t-1} + \beta_4\Delta y_{t-1}^i + \beta_5\Delta oil_{t-1} \\ &\quad + \beta_6\Delta r_{t-1} + \mu_t^i \qquad (4.1) \\ \Delta\tilde{\kappa}_t^i &= \phi^i + \phi_T^i \cdot trend^i + \left(\phi_1 + \phi_2\chi_t^i + \phi_3\alpha_t^i + \phi_4 m_t^i\right)\Delta\hat{e}_t + \phi_5\Delta y_t^i + \nu_t^i\end{aligned}$$

where Δ indicates log first differences with the exception of the cost of capital, r, for which it indicates level first differences.[1] Industry level real investment is I. The share of exports is represented by χ, the imported input share by α, and the average markup by $\tilde{\kappa}$, all of which are industry level variables. The exchange rate variable, $\hat{e}$, is the permanent component of the real value of the dollar (*i.e.* $\Delta\hat{e} > 0$ is a dollar appreciation). Real industry sales, y; the cost of capital (10-year U.S. Treasury note rate), r; and the price of other inputs (proxied by the real price of oil), oil, are also included as explanatory variables for investment. The coefficients on the industry dummy variables are captured in β^i. In the markup equation, ϕ^i is the coefficient on an industry dummy variable, ϕ_T^i is the coefficient on the industry trend variable, and m_t^i is import penetration as measured by the ratio of industry imports to domestic consumption. First differences are used to control for the nonstationarity of the permanent component of the real value of the dollar. All time subscripts are $t-1$ due to the one-period-time to build assumption (investment decisions that appear in the data at time t were made at time $t-1$ using the best forecast of expected future variables at time $t-1$). The industry superscript is i.

Even if one had the exact data of Campa and Goldberg (1999), replicating their methods would still present some problems. First, the authors chose the 3SLS method of estimation to allow for the simultaneous determination of investment and markups with respect to changes in the exchange rate, but their formulation of the system is quite different from the textbook approach. In Equation (4.1), the markup variable enters the investment equation in levels form ($\tilde{\kappa}_{t-1}^i$), while in the markup equation it is defined in difference form ($\Delta\tilde{\kappa}_t^i$). The fact that the markup variable in the investment equation is lagged, inverted, and used in interaction terms adds an additional layer of complexity. In addition, the authors say that their procedure "instruments interest rates to control for their possible endogeneity," and that they "use as instruments the exchange rate changes and lagged values of interest rates." They are not clear as to whether the problem of endogeneity arises between the interest rate and investment, or between the interest rate and the exchange rate, or both. An additional problem is that they provide no additional information whether the exchange rate changes that are used as instruments are calculated using permanent or actual exchange rates, as to whether the interest rate lags are in difference or level form, or how many lags are used. They also do not say whether they use all other exogenous variables as instruments, thereby making the exchange rate changes and lagged interest rates excluded instruments. In general, the authors are

[1] The theoretical underpinnings of this empirical model are discussed in Chapter 2.

Table 4.1. Replication of 3SLS: Equations Corrected for Serial Correlation

	Benchmark[a]	BN (reu)	HP (reu)	BN (Fed)	HP (Fed)
Investment (ΔI_t^i)					
$(\tilde{\kappa}_{t-1}^i)^{-1}\Delta\hat{e}_{t-1}$	0.337	-0.019	0.214	-0.098	-0.234
	(1.25)	(-0.07)	(0.29)	(-0.26)	(-0.26)
$\chi_{t-1}^i(\tilde{\kappa}_{t-1}^i)^{-1}\Delta\hat{e}_{t-1}$	-6.218*	-2.262	0.423	-2.492	-0.302
	(1.79)	(-1.03)	(0.08)	(-0.85)	(-0.05)
$\alpha_{t-1}^i(\tilde{\kappa}_{t-1}^i)^{-1}\Delta\hat{e}_{t-1}$	5.634	3.472	-8.552	5.045	-7.606
	(1.28)	(1.00)	(-0.93)	(1.11)	(-0.65)
Δy_{t-1}^i	0.535**	0.838**	0.836**	0.878**	0.584**
	(5.75)	(4.48)	(4.75)	(5.23)	(3.98)
Δoil_{t-1}	0.052**	-0.161**	-0.142**	-0.156**	-0.142**
	(2.17)	(-2.80)	(-2.54)	(-2.84)	(-2.51)
Δr_{t-1}	-0.169**	0.030**	0.030**	0.029**	0.033**
	(-2.31)	(2.73)	(2.73)	(2.86)	(3.01)
$\hat{\rho}$ [b]		-0.118*	-0.100	-0.102*	-0.102*
		(-1.82)	(-1.63)	(-1.74)	(-1.76)
$\hat{\rho}_{robust}$ [c]		-0.122	-0.104	-0.104	-0.090
		(-1.36)	(-1.29)	(-1.31)	(-1.18)
Markup ($\Delta\tilde{\kappa}_t^i$)					
$\Delta\hat{e}_t$	-0.190**	0.033	0.192*	0.074	0.121
	(-2.09)	(0.95)	(1.69)	(1.61)	(0.98)
$\chi_t^i\Delta\hat{e}_t$	2.588**	0.243	0.318	0.259	-0.051
	(2.48)	(1.09)	(0.46)	(0.89)	(-0.07)
$\alpha_t^i\Delta\hat{e}_t$	-2.232	-1.289	-5.793**	-2.326**	-4.033
	(-1.64)	(-1.60)	(-2.18)	(-2.22)	(-1.33)
$m_t^i\Delta\hat{e}_t$	-0.033	0.377	1.558**	0.597*	1.294
	(-0.08)	(1.54)	(2.01)	(1.89)	(1.47)
Δy_t^i	0.184**	0.216**	0.193**	0.190**	0.181**
	(4.60)	(8.40)	(7.70)	(8.27)	(9.22)
$\hat{\rho}$ [b]		-0.137**	-0.140**	-0.129**	-0.130**
		(-2.30)	(-2.43)	(-2.28)	(-2.48)
$\hat{\rho}_{robust}$ [c]		0.281	0.281	0.300	0.236
		(0.88)	(0.93)	(0.97)	(0.87)
N		300	320	340	360
Period		1979-93	1978-93	1977-93	1976-93

Notes: $*p < 0.10$, $**p < 0.05$; t statistics in parentheses; $\hat{e}$ is the permanent component of the real value of the dollar.

[a] Benchmark results are Campa and Goldberg (1999).

[b] $\hat{\rho}$ is the estimated coefficient for the $AR(1)$ term included in the E-Views 3SLS system estimation.

[c] $\hat{\rho}_{robust}$ is an estimate of the serial correlation coefficient, which is robust to heteroskedasticity. This test for serial correlation is described in the text.

very careful in their verbage concerning variable descriptions,[2] so I interpret these instruments as changes in the *actual* exchange rate (not the permanent component) and lagged values of the *level* of the interest rate.

The third and fourth lags were chosen for the replication because, according to initial tests, they were most likely to be correlated with the instrumented interest rate and orthogonal to the error term. In Campa and Goldberg (1995), the authors also estimated an investment function that included the exchange rate and an interest rate. In that paper, they were very clear that the problem of endogeneity arises between the interest rate and investment. They also clearly indicated that the lagged values of the interest rate were excluded instruments, so all other exogenous variables are treated as included instruments. I take an historical approach to interpreting what Campa and Goldberg did in the 1999 paper and assume that their treatment of instrumental variables is similar to that of the 1995 paper. Lastly, in the regression table notes Campa and Goldberg (1999) state that each equation in the system is corrected for first order serial correlation, but they do not mention which method is used. Since they refer to the correction as one that is performed upon the equations in the system (as opposed to upon the standard errors), I include an autoregressive, $AR(1)$, term when performing the system estimation in E-Views.

The first attempt at replication involves determining the proper choice of data for the permanent component of the exchange rate. Recall from the section on permanent exchange rates in Chapter 3, the difficulties associated with replicating the method of decomposing the exchange rate into its permanent and transitory components. That section also noted the differences in the data available for the current analysis and that used in the benchmark study. In order to determine which available series for the permanent component of the exchange rate is most appropriate to use for replication, Equation (4.1) is estimated with four different options for the permanent component. The four options are the permanent components as determined by the B-N decomposition and the H-P filter for both the IFS (reu) series and the Fed (H.10) series. These results are compared to the results in Campa and Goldberg (1999)[3] and are reported in Table 4.1.

---

[2]Throughout the paper, Campa and Goldberg (1999) often make clear delineations between permanent and actual exchange rates and between measures of variables in levels and differences

[3]Although, Campa and Goldberg (1999) do not mention a change in how they measure the exchange rate, their discussion of the results suggests that they switched the real value of the dollar to an exchange rate variable measured in terms of domestic currency per unit of foreign currency. This difference suggests that Campa and Goldberg's reported signs on the coefficients of the exchange rate interaction terms should be reversed for comparability, which I do for the benchmark estimates in Table 4.1

Similar to the benchmark result, all of the estimated coefficients for the exchange rate interaction term, $(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$, are statistically insignificant. Only the coefficient using the H-P IFS exchange rate (0.214) carries the same sign as Campa and Goldberg (0.337). For the export share interaction term, $\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$, the estimated coefficients for the two B-N exchange rate series (-2.262 and -2.492 for the IFS and Fed series, respectively) are both negative as reported in the benchmark (-6.218), but they are statistically insignificant. The coefficients for the two H-P series (0.423 and -0.302 for the IFS and Fed series, respectively) are insignificant, and the IFS estimate is positive. For the imported input share interaction term, $\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$, all of the exchange rate series produce insignificant coefficient estimates, but only the two B-N series carry the expected positive sign (3.472 and 5.045 for the IFS and Fed series, respectively), as reported in Campa and Goldberg (5.634).

Regardless of the permanent component tested, I find no evidence of a statistically significant exchange rate effect on investment using the 3SLS method as suggested by Campa and Goldberg (1999). The estimated coefficients for the control variables, on the other hand, tend to perform at least as well as Campa and Goldberg's in terms of statistical significance. For the sales accelerator variable, Δy^i_{t-1}, all of the estimated coefficients are positive and of the same level of significance as that of the benchmark (0.535). Using the H-P Fed series yields an accelerator coefficient (0.584) that is very close in terms of magnitude; while the other three series yield estimates that range from 0.836 to 0.878 (which is at least of a similar order of magnitude). My estimates for the coefficients on the price of oil variable and the exchange rate yield an interesting contrast to those of Campa and Goldberg (1999). First, note that all of the coefficients have a similar level of significance to the benchmark results. What is striking is that my coefficient estimates for oil have a narrow range of -0.161 to -0.142, which is remarkably similar in terms of sign and magnitude to Campa and Goldberg's reported estimate for the interest rate coefficient (-0.169). In addition, my coefficient estimates for the interest rate have a narrow range of 0.029 to 0.033, which is remarkably similar in terms of sign and magnitude to Campa and Goldberg's reported estimate for the oil coefficient (0.052).

The contrast in results for the oil and interest rate coefficients suggests that Campa and Goldberg (1999) may have inadvertently interchanged the estimates for these two variables. The authors provide no discussion of these estimates, so it is difficult to say for sure. As a proxy for the price of other inputs, one would expect the sign on the price of oil variable to be negative, which is supported by my coefficient estimates. On the other hand, investment theory suggests that the sign on the interest rate variable should be negative, which is in conflict with my coefficient estimates. Two factors arise, however, when assessing the coefficients on the interest rate. First, the interest rate variable is notorious for non-theoretical behavior in the empirical literature on investment (see for example, Bosworth (1993) and Fazzari (1993)). Second, Campa and Goldberg apparently used a nominal interest rate to explain real investment, which may exaggerate such impishness.

In the markup equation, the estimated coefficients for the non-interacted exchange rate term, $\Delta\hat{e}_t$, are all positive and mostly insignificant (with the exception of the H-P IFS estimate of 0.192, which is significant at 10%). In contrast, Campa and Goldberg (1999) estimate this coefficient as -0.190 with a significance level of at least 5%. For the export share exchange rate interaction term, $\chi_t^i\Delta\hat{e}_t$, the benchmark point estimate is 2.588 with a significance level of 5%. My estimates, while mostly positive (with the exception of the H-P Fed estimate), are all statistically insignificant. My coefficient estimates for the imported input interaction term (ranging from -5.793 to -1.289) all have the same sign as Campa and Goldberg's estimate of -2.232; but, while their estimate is insignificant, I find two of the coefficients to be significant at 5% (-5.793 and -2.326 for the H-P IFS and B-N Fed series, respectively). The H-P IFS and B-N Fed series also yield coefficients (1.558 and 0.597, respectively) that are significant at least at 10% for the import competition interaction term, $m_t^i\Delta\hat{e}_t$. The estimates for the B-N IFS and H-P Fed series of this coefficient are also positive, but insignificant. Together, these results differ in terms of sign and significance from the insignificant estimate (-0.033) of Campa and Goldberg (1999).

Similar to the investment equation, my results for the non-exchange rate control variables (in this case, just Δy_t^i) perform more consistently across the different exchange rate series. My results yield a narrow range of estimates (0.181 to 0.216) that are very close to the benchmark point estimate (0.184) in terms of sign, magnitude, and significance. Although the results for the industry dummy variables and time trends are not reported, I would like to emphasize that the coefficients are rarely significant. Not a single industry dummy variable coefficent is statistically significant in any of the investment equation estimates. In the markup equation, only the dummy variables and the time trends for the Tobacco, Lumber and Chemical industries show evidence of statistical significance.[4]

[4] Given a 10% level of significance, the following coefficients are statistically significant: for the B-N IFS series, time trend for Tobacco; for the H-P IFS series, dummies and time trends for Tobacco, Lumber and Chemicals; and for both the the Fed series, dummies and time trends on Tobacco and Chemicals.

After the results for the coefficients in each equation, Table 4.1 also reports two different estimates of the serial correlation coefficient. The first estimate, $\hat{\rho}$, is the estimated coefficient for the $AR(1)$ term included for each equation in the E-Views 3SLS system estimation. In the investment equation this coefficient has a narrow range of estimates (-0.118 to -0.100), and mostly they are significant at the 10% level (the exception is for the H-P IFS series). For the markup equation, the estimates range from -0.140 to -0.129 and all are significant at 5%. The combination of these results suggests that serial correlation is present in the estimation equations and should be accounted for in the regressions. Problems arise in relying on this conclusion (and in using 3SLS altogether), however, when the data exhibit heteroskedasticity. First, 3SLS estimates become inconsistent in the presence of heteroskedasticity, so it is impossible to use a robust test for serial correlation in such a system estimation. What can be done, however, is to use the robust test for serial correlation suggested by Wooldridge (2010) on each individual equation.[5] The test statistic, in this case, is the robust estimate of the serial correlation coefficient, $\hat{\rho}_{robust}$. These results present an entirely different picture, as not a single equation shows evidence of the presence of first order serial correlation when taking into account heteroskedasticity. By dropping the industry dummy variables from each equation, and running a standard fixed effects panel data estimation of each equation, a modified Wald test for groupwise heteroskedasticity can be performed, as outlined in Baum (2001). The results from such a test provide strong evidence for the presence of groupwise heteroskedasticity in all cases for each equation.[6]

Overall, I find no evidence of an exchange rate effect on investment when attempting to replicate Campa and Goldberg's baseline results for the U.S. While they consistently find the expected signs on the exchange rate terms across four countries, my results suggest that the signs on these coefficients could be quite sensitive to the choice of exchange rate series and the choice of decomposition method to obtain the permanent component. If anything, the results for the investment equation suggest that the two H-P series should not be used in additional replication efforts, because they consistently yield estimates with the opposite sign from those of Campa and Goldberg (1999).

The difference in my results for the markup equation are more difficult to digest. First, Campa and Goldberg provide no theoretical justification for the markup equation specification. As

[5]As noted in Wooldridge (2010), a nice feature of this test is that it does not require the assumption of strict exogeneity for the regressors.

[6]The null hypothesis is that of homoskedasticity, and the p-value in every case was 0.0000.

such, they do not seek to explain the relationship between markups and the exchange rate, rather they rely on the markup equation to control for the potential simultaneity between the two. As a result, the authors give very limited attention to the results for the markup equation. In their brief discussion of the markup results for all countries, however, they imply that a significant coefficient on $\Delta\hat{e}_t$ is what provides the evidence that the markup is dependent on the exchange rate. With the exception of the estimate for this coefficient using the H-P IFS series (which has the opposite sign of the benchmark and is only significant at 10%), I find no evidence of the exchange rate affecting the markup in this manner. In contrast, my results seem to corroborate the earlier findings of Campa and Goldberg (1995) which show very little statistical support for an effect of the exchange rate on the markup for all U.S. manufacturing industries.

Lastly, Campa and Goldberg (1999) do not discuss their reasons for correcting each equation for serial correlation,[7] nor do they provide any diagnostic tests for departures from i.i.d. errors. Since they do not mention heteroskedasticity at all, it seems quite possible that the authors failed to account for it in their analysis. If this is true, then any gain in efficiency from using 3SLS becomes moot due to the presence of heteroskedasticity. The questions that arise from these findings cast some doubt on the methodology used and the reliability of the results within that study. Even without the actual data and knowledge of the exact methods used in Campa and Goldberg (1999), the results presented here certainly raise questions about the robustness of their findings. In footnote 23 on page 299, the authors mention that results from two-stage least squares (2SLS) estimation, which do not use instrumented markups, yield qualitatively similar results. Given this statement, I refocus my efforts to single equation estimation of the investment function.

The preceding analysis represents my best effort for actual replication, given the information available in the original study. In the next analysis, I am not as concerned with *reproducing* the results from Campa and Goldberg (1999). Rather, I am more concerned with creating a baseline for comparison, which reflects the characteristics of my own data, yet is still performed in the spirit of the original study. Since I am mainly concerned with the effect of the exchange rate on investment, and because I find limited statistical evidence for an exchange rate effect on the markup; I limit the analysis to the investment equation. In addition, I use only the permanent component of the exchange rate from a B-N decomposition of the Fed's real value of the dollar. I choose this series,

[7] In Table 4.13 of the Appendix, I present the results of the 3SLS procedure without correcting for serial correlation. In general, these results are no closer to those of Campa and Goldberg (1999).

because the B-N decomposition yields investment equation results that at least have the same sign as Campa and Goldberg (1999), and because it has a longer time component than the IFS series.

Table 4.2. IV/GMM Estimation of Investment Equation

	(1) 2SLSIV	(2) 2SLSIV Robust	(3) FEGMM	(4) FEGMM Extra
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$	-0.134	-0.134	-0.110	0.030
	(-0.33)	(-0.35)	(-0.29)	(0.09)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$	-2.762	-2.762	-3.292	-6.446**
	(-0.90)	(-0.85)	(-1.02)	(-2.19)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$	6.297	6.297	5.604	6.517
	(1.32)	(1.42)	(1.26)	(1.62)
Δy^i_{t-1}	0.575***	0.575***	0.539***	0.495***
	(3.95)	(3.78)	(3.62)	(3.49)
Δoil_{t-1}	-0.140*	-0.140**	-0.151**	-0.169***
	(-1.91)	(-2.28)	(-2.49)	(-3.90)
Δr_{t-1}	0.023	0.023	0.024*	0.023**
	(1.40)	(1.60)	(1.72)	(2.63)
Tests of identification and endogeneity (robust to heteroskedasticity)				
Underidentification Test[a]			73.474***	139.626***
p-value			0.0000	0.0000
Overidentification Test[b]			3.855	52.583***
p-value			0.1455	0.0023
Exogeneity Tests[c]				
$\left(\tilde{\kappa}^i_{t-1}\right)^{-1}\Delta\hat{e}_{t-1}$			0.389	2.037
p-value			0.5326	0.1535
$\chi^i_{t-1}\left(\tilde{\kappa}^i_{t-1}\right)^{-1}\Delta\hat{e}_{t-1}$			3.560*	0.107
p-value			0.0592	0.7442
$\alpha^i_{t-1}\left(\tilde{\kappa}^i_{t-1}\right)^{-1}\Delta\hat{e}_{t-1}$			1.661	8.323***
p-value			0.1974	0.0039
Endogeneity Test[d]			6.848***	3.299*
p-value			0.0095	0.0693
N	360	360	360	360
Period	1976-1993	1976-1993	1976-1993	1976-1993

Notes: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; t statistics in parentheses; $\hat{e}$ is the permanent component of the real value of the dollar.

[a] Kleibergen-Paap rk LM statistic; H_o : equation is underidentified.

[b] Hansen J statistic; H_o : correct model specification and valid overidentifying restrictions.

[c] C statistic; H_o : instrument tested is exogenous.

[d] C statistic; $H_o : \Delta r_{t-1}$ actually can be treated as exogenous.

In Table 4.2, I present the results from four different different regressions of the investment equation, using instrumental variable/generalized method of moments techniques. For this exercise, I utilize the *ivreg2* routine in Stata as developed by Baum et al. (2010). This routine provides several advantages for single-equation, linear, IV estimation due to the wealth of post-estimation diagnostics associated with it. The robust test of serial correlation performed in the previous analysis suggests no autocorrelation, so I discard the resulting adjustment to the equation. I treat the interest rate as endogenous in the same manner as the previous estimations in order to maintain comparability. The *ivreg2* routine allows me to test this assumption and the validity of the instrument set. In order to set a baseline for the estimation equation, I first estimate a standard two-stage least squares instrumental variable (2SLSIV) regression on the investment equation. These results are reported in Column (1) of Table 4.2. First, the coefficient estimates for the exchange rate terms are all similar in terms of sign, magnitude, and significance as the 3SLS estimates for the B-N Fed exchange rate series. Second, the 2SLSIV estimation yields a coefficient for the sales accelerator term that is extremely close to that reported by Campa and Goldberg (1999). Last, the estimated coefficients for the oil and interest rate variables are similar in sign and magnitude to my results for the system estimation, which corroborates my suspicion that Campa and Goldberg (1999) may have misreported their estimates.

In the previous analysis, I mentioned the likelihood of the presence of groupwise heteroskedasticity. The validity of this test in an IV context is unverifiable; however, after the initial *ivreg2* estimation, I can perform various tests of heteroskedasticity that are clearly valid in an IV approach. Using the procedure outlined in Baum et al. (2003), all of the tests strongly suggest the presence of heteroskedasticity with all p-values ≤ 0.0001. I also perform the Arellano-Bond test of autocorrelation after the estimation using the *abar* command developed in Roodman (2009). Although this test requires a large-N panel, it is the only postestimation test for serial correlation that I am aware of for panel data IV estimation. The null hypothesis is no first order autocorrelation, and the result for the z statistic is -1.07 with a p-value of 0.2844. At this point, all of the evidence suggests that the standard errors should be robust to heteroskedasticity, only.

In Column (2), I present the results for a 2SLSIV estimation with statistics that are robust to the presence of arbitrary heteroskedasticity. The major difference in the estimates with this correction is that the significance level of the oil variable is now at 5%. As noted in Baum (2006), when faced with non-i.i.d. errors, the results in Column (2) are essentially the equivalent to that of a two-step generalized method of moments (GMM) estimation using a suboptimal weighting matrix. To rectify this situation, I re-estimate the equation using the optimal weighting matrix and present the results of the feasible efficient two-step generalized method of moments (FEGMM) estimator in Column (3). The major difference in the estimates between the robust 2SLSIV and FEGMM estimates is that the significance of the interest rate variable is now at 10%. Starting with this specification,[8] I also report the results of four standard post-estimation tests for IV techniques that are also robust to the presence of heteroskedasticity.

The first test utilizes the Kleibergen-Paap rk LM statistic to test for underidentification. The rejection of the null indicates that the rank condition for IV estimation holds, which ensures that there is enough correlation between the instruments and the endogenous variables to yield unique parameter estimates. The second test utilizes a Hansen J statistic to test the validity of the overidentifying restrictions. For the FEGMM estimation, I fail to reject the null hypothesis of correct model specification and valid overidentifying restrictions. This result suggests that taken together, the instrument set (both included and excluded) is orthogonal to the error term. Since the exchange rate interaction terms are also interacted with the markup, one would suspect a rejection of the null for this test if the markup should be treated as endogenous. Following the overidentification test, I provide individual exogeneity tests for each of the three interaction terms. This difference-in-Sargan test, utilizes a C-statistic to test the orthogonality condition of a suspect instrument. Of the three interaction terms, only the one weighted by the export share rejects the null hypothesis that the instrument is exogenous. Both the Hansen J and C-statistics are robust to the presence of heteroskedasticity. This finding combined with the results of the overidentification and individual exogeneity tests raises some doubt as to whether the markup actually is creating any simultaneity bias in the regression results. The final test presented is an endogeneity test of whether the interest rate can be treated as exogenous. As with the exogeneity tests, this test utilizes a C-statistic. The result of the test suggests that the interest rate should indeed be treated as endogenous in the FEGMM specification.

Although efficient, the results of the FEGMM estimation are qualitatively similar to that of the robust 2SLSIV approach. In addition, not a single industry fixed effect is found to be statistically significant in any of the first three regressions. More importantly, I want to emphasize that not a single exchange rate interaction variable is found to be statistically significant, either. By

[8] The results of these tests are exactly the same for the 2SLSIV estimation reported in Column (2), because the instrument set is the same as that of the FEGMM estimation. I purposely omit the statistics for 2SLSIV in order to reduce confusion and avoid repetition.

using single equation techniques and by not instrumenting the markup, I do not seem any closer to replicating the results of Campa and Goldberg (1999). On the other hand, I will present one more estimation in this section on single equation IV analysis that may shed some light on this mystery.

Recall from the system estimation in the initial attempt at replication that the benchmark study uses a 3SLS estimation. By doing so, the instrument set for the second stage estimation of the investment equation includes several variables in addition to the ones for a single equation IV estimation – namely, all of the regressors in the markup equation. The post-diagnostics of the FEGMM regression indicate the excluded instrument set with only the third and fourth lags of the interest rate and the actual exchange rate changes as excluded instruments is a good one. But what of the much larger instrument set that is used in the 3SLS estimation? As an imperfect sensitivity test,[9] I run an extra FEGMM regression with the expanded set of excluded instruments. These results are presented in Column (4) and are astonishingly close to that of Campa and Goldberg (1999). The accelerator effect, per usual, is similar in magnitude and significance and the coefficient estimates for the oil variable and impish interest rate seem to be switched in comparison to Campa and Goldberg (1999). Again, not a single industry effect is statistically significant. More astonishing are the results for the export and import channels of the exchange rate as indicated in the coefficient estimates for the latter two exchange rate interaction terms. The results here are extremely similar to that of the benchmark in terms of both statistical significance and magnitude. On the other hand, the results of the Hansen J statistic for the test of overidentification leads to a rejection of the null hypothesis at the 1% level of significance. Baum (2006) notes that such a strong rejection for the J test calls into question the independence of the instruments and the disturbance process.

In comparing the results of the 3SLS estimates in Table 4.1 to the single investment equation estimates of Table 4.2, my results suggest that source of the bias in the single equation estimates for the exchange rate terms was not a result of simultaneity with the markup variable, but rather was a result of an improper instrument set created by the system estimation. In addition, I would like to draw your attention to the change in the C statistic associated with the endogeneity test that arises when the extra instruments are added to the FEGMM estimation. The value of the C statistic drops by half and can no longer be rejected with 95% confidence. Granted, the p-value of 0.0693 still implies that the null hypothesis of an exogenous interest rate could be rejected with

[9]Econometrically, it is unclear whether the post-diagnostics from a single equation IV are comparable to what could be developed for a system estimation. To my knowledge, no such tests have been developed for system estimation.

90% confidence; but the result does provide an opportunity to discuss the motivation for treating the interest rate as endogenous in the first place. Campa and Goldberg (1999) state that their reason for instrumenting the interest rate is to control for its potential endogeneity. They provide no other discussion of the topic, nor do they provide any evidence supporting such treatment. In the empirical applications of the investment function literature, the interest rate or cost of capital variable is rarely treated as endogenous to the system, unless of course there is a strong argument supporting the presence of simultaneity bias (for a review, see Chirinko (1993)). In addition, any test for endogeneity is dependent upon the set of instruments used in the estimation, which for this estimation are poor. In static, linear, IV panel data estimation a typical starting point for the excluded instrument set is to use lagged values of the endogenous regressor.[10] Seemingly in Campa and Goldberg (1999), the authors do not take such an approach. While the post-estimation tests reported in column (3) of Table 4.2 support treating the interest rate as endogenous in that particular regression, the fact that I am having such difficulty, overall, in reproducing the benchmark results does raise the question as to whether instrumenting the interest rate is a useful endeavor.

Lastly, I would like to address another concern regarding Campa and Goldberg (1999) that has received quite a bit of attention in the recent literature on panel data analysis: cross-sectional (or spatial) dependendence. Much of this research indicates that cross-sectional (C-S) dependence is widely prevalent in macroeconomic panel data, yet it is commonly ignored in econometric analysis (see, for example, Phillips and Moon (1999)). Pragmatically, one clearly would expect a sample of U.S. manufacturing industries to exhibit some sort of cross-sectional dependence, since they would likely experience similar shocks to the U.S. economy. Recent advances in testing allow one to test for the presence of C-S dependence in the situation where $N > T$, as I have in the replication data.[11] All three of the tests provided by Hoyos and Sarafidis (2006) strongly indicate the presence of C-S dependence, when they are performed after a standard fixed effects or random effects estimation of the single equation investment model. An additional complication that arises from this result is that many of the available tests for and methods to correct for the presence of C-S dependence rely on the assumption of strict exogeneity of the independent variables, as noted in Pesaran et al. (2008). This complication adds further intrigue to the question of treating the interest rate as endogenous.

---

[10] In dynamic panel data estimation where one regressor is the lag of the dependent variable (both of which are measured in log differences), consistent IV estimation often relies on using lagged values of the dependent variable measured in levels.

[11] For a brief survey of methods and an overview of the *xtcsd* command in Stata, see Hoyos and Sarafidis (2006).

In concluding the replication section of this chapter, I will make a few remarks on what was accomplished from this exercise. First, the results for the U.S. presented by Campa and Goldberg (1999) do not readily lend themselves to replication. Using multiple measures of the permanent component of the exchange rate and various estimation techniques, I am unable to consistently reproduce their results. Second, the literature on IV/GMM estimation techniques and diagnostics has expanded rapidly since Campa and Goldberg (1999). This expansion has added several econometric tools and guidelines to the practitioner's toolbox. Using these tools, I find that the authors might have placed priority on the wrong set of departures from OLS assumptions. The tests presented here suggest that priority should be placed on addressing heteroskedasticity and cross-sectional dependence. Although there is a rich literature which links markup behavior to the exchange rate (see, for example, Feinberg (1989) and Fisher (1989)), I find very little econometric evidence for treating the markup variable as endogenous in my dataset. I propose that Campa and Goldberg (1999) might have inappropriately corrected for first order serial correlation and tried to address endogeneity and simultaneity at the expense of robustness in their results.

4.2 Extension

In this section, I take what was learned in the replication process and attempt to address these concerns using the expanded dataset. Here, I place priority on addressing issues of heteroskedasticity and C-S dependence, I perform a more thorough analysis of serial correlation, and I treat the interest rate and markup variables as exogenous in the econometric analyses. While this may be an imperfect approach, it does allow me to attack these particular problems while forming an empirical benchmark to address other questions of interest.

Recall, the expanded dataset updates the time period of analysis to 1973-2005.[12] In doing so, I update the industry measures of external orientation to reflect the 2002 Benchmark I-O accounts as the input-output matrix used in their construction. For comparison to Campa and Goldberg (1999), the data include industry measures of the markup and real sales. The extended dataset is limited to only 19 U.S. manufacturing industries, because I drop the tobacco industry due to its drastically different markups. In the extended analysis I rely on the broad, trade-weighted real value of the dollar index for the economy-wide exchange rate, but I also use the industry-specific exchange rate indexes to test the sensitivity of the regression results to the choice of exchange rate

[12] A full description of the extended dataset is found in section 3.1.2.

variable. Again for the sake of comparison, I include measures of the real price of oil and the interest rate which are time-varying but do not vary by industry. The data also include other measures of the interest rate for additional sensitivity tests.

4.2.1 Non-i.i.d. Errors in Panel Data

With the considerable attention that has been given to the treatment of non-i.i.d. errors for panel data within the recent literature (*e.g.* Cameron et al. (2006); Hoechle (2007); Thompson (2009); Peterson (2009); Reed and Ye (2011)), I think it is important to provide a few remarks on the choice of estimation techniques for this analysis. Much of the recent research in this area relies on the results of Monte Carlo simulations to provide practical guidelines to the researcher when faced with various combinations of the "unholy trinity" of violations to OLS assumptions: heteroskedasticity, serial correlation, and C-S dependence. Although the recent additions to the literature are extremely helpful in many settings, the industry-level, macro-oriented data used in this analysis present some particular obstacles.

First of all, including macrofactor variables that vary across time but not individuals (*e.g.* the price of oil and the interest rate) limits the choices of estimation technique and post-estimation testing. Baum (2006) and Thompson (2009) note that including time fixed effects or performing two-way fixed effects (FE) estimation is not warranted, because the macrofactor variables would be collinear with the time effects. In addition, Wooldridge (2010) shows that these variables prevent the usage of a Hausman-type test comparing random effects (RE) and FE estimators, which is a standard post-estimation diagnostic for FE estimation of panel data.

Second of all, the dimension of the full sample ($N = 19$ and $T = 30$) adds an additional set of restrictions to the choice of estimation; not to mention, splitting the full sample into industry subsets yields even samller dimensions ($N = 9$ and $N = 10$) for the different sub-samples used. One of the most useful developments in the recent literature on panel data estimation is robust inference with two-way clustered standard errors, as suggested by Cameron et al. (2006), Peterson (2009), and Thompson (2009). As long as there are sufficient clusters, this method would allow for both an industry effect and a time effect and result in unbiased standard errors. The limited number of clusters in the industry-level data presented here, particularly the small number of industries, raises questions about the validity of using such an approach. Cameron et al. (2006), Peterson (2009) and Thompson (2009) all note that the asymptotics of two-way clustered errors depends upon the assumption that the smallest number of clusters approaches infinity ($\min\{N, T\} \to \infty$).

While two-way clustered standard errors can produce moderately low rejection rates of true null hypotheses when faced with small sample cluster dimensions,[13] the data dimension for this analysis is at the margin. This marginal cluster dimension for the full sample, then, would prevent any divisions in the industries for comparisons between different sample splits.

The traditional treatment for heteroskedasticy and C-S dependence is feasible generalized least squares (FGLS), as suggested by Parks (1967) and Kmenta (1997). As noted in Beck and Katz (1995), however, the standard errors produced by FGLS for common, small sample sizes are notoriously biased downwards, which leads to over-optmistic hyptothesis testing. In particular, they find that the FGLS treatment of C-S dependence leads to significant levels of overconfidence. In response, they develop panel corrected standard errors (PCSE) for use with OLS estimation. The authors argue that PCSE estimation yields more plausible results for data with ten to twenty panels and ten to forty periods per panel. My extended dataset with nineteen panels and thirty time periods falls right in this range. Estimation using FGLS and PCSE also provide a methodology to correct for first order serial correlation. In both cases, a Prais-Winsten (PW) transformation is first performed in order to eliminate the serial correlation. Both estimation methods allow for the choice between a common and a unit-specific serial correlation coeffcient. Beck and Katz (1995) strongly assert that transforming the data for each panel unit, in order to obtain a unit-specific error process, leads to additional overconfidence of standard errors when performing estimation by FGLS; they argue that a common correlation coefficient is the better option. They do note, however, that the overconfidence from using a panel-specific coefficient can disappear when the time component is at least 30, which is what is present in the extended dataset.

In Reed and Ye (2011), the authors provide an additional recommendation. For $T > N$ they suggest that the choice of estimation technique should be based on the priority of the researcher between efficiency and constructing accurate confidence intervals. If efficient estimators have priority, the authors recommend using FGLS. If accurate confidence intervals have priority, they recommend OLS with PCSE or OLS with heteroskedasticity and cross-sectional dependence robust standard errors (*i.e.* clustering on the time component). An additional contribution, and one that is applicable to the data used in this analysis, is that the authors determine that a ratio of $T/N \geq 1.5$ is generally sufficient to meet the asymptotic requirements for efficiency ($T/N = 1.58$ in the full sample and the sample splits only increase the ratio). This result provides a bit more leeway for

---

[13] Cameron et al. (2006) and Thompson (2009) find acceptable rejection rates at $N = 20$ and $T = 20$ and $N = 25$ and $T = 25$, respectively.

the small sample researcher than the advice of Beck and Katz (1995), who recommended that T be "considerably" larger than N.

The main drawback to the previous three methods is that they do not address the presence of higher order serial correlation. For that, one must turn to Driscoll-Kraay standard errors (DKSE), as suggested in Driscoll and Kraay (1998). Hoechle (2007) provides a nice overview of DKSE and compares the method to that of FGLS and PCSE. The DKSE method is essentially a weighted least squares estimation, which uses a nonparametric covariance matrix estimator that is robust to heteroskedasticity, C-S dependence and various forms of serial correlation. Similar to a Newey-West estimation (Newey and West, 1987), one must choose a kernel and a bandwidth that indicates the lag length up to which the errors may be serially correlated. Hoechle (2007) notes that this constraint necessarily limits the procedure to consideration of moving-average errors in the residual, but he also provides support for their approximation to autocorrelated processes in the error term. Although the main advantage attributed to DKSE is in the case where $N > T$ (because the covariance matrix estimator is consistent regardless the size of N), it also seems that this method is beneficial to those who face serial correlation of a higher order. Lastly, Hoechle provides a basic plug-in estimator for the choice of bandwidth that is based on the first step of the procedure developed in Newey and West (1994). This plug-in estimator, however, does not necessarily provide the optimal choice of lag length, rather it serves as a starting point for practicioners. The author notes that his simple rule tends to choose a bandwidth that might often be too small.

4.2.2 Comparison of Econometric Methods

As described in the previous subsection, the recent advances within the literature still leave the annual-data, macro-oriented, exchange rate researcher with a brittle foundation when it comes to estimation strategy. In the initial analysis I will take advantage of the efficiency of FGLS in order to test the sensitivity of the results to different choices in data and to make some basic comparisons to the results in Campa and Goldberg (1999). Interpretation of these results will proceed with caution, noting that the standard errors will likely be biased downwards. Then, I will perform the PCSE and DKSE methods and compare the results to a subset of the FGLS results, in order to get a more realistic picture of the performance of the model.

As a starting point, I use a basic formulation of the investment equation in Campa and Goldberg (1999):

$$\Delta I_t^i = \beta_0 + \left(\beta_1 + \beta_2\chi_{t-1}^i + \beta_3\alpha_{t-1}^i\right)\left(\tilde{\kappa}_{t-1}^i\right)^{-1}\Delta e_{t-1} \\ + \beta_4\Delta y_{t-1}^i + \beta_5\Delta oil_{t-1} + \beta_6\Delta r_{t-1} + \mu_t^i \tag{4.2}$$

where the main difference from Equation (4.1) is the replacement of the industry dummy variables with a single intercept.[14] I remove the hat from the real value of the dollar, e, to indicate that I will test both the actual changes in the exchange rate and the permanent component of these changes. As a result of the findings in the replication section above, I ignore any potential simultaneity bias from the markup variable, so there is no additional equation. In this formulation (as in the standard approach), the domestic channel and the export channel cannot be entirely disentangled. From Equation (2.24), one can see that the coefficient β_1 estimates only part of the domestic channel. The coefficient β_2, on the other hand, estimates a combination of the export channel with the remaining portion of the domestic channel. Since the magnitude of β_1 is likely small, the coefficient β_2 likely can be interpreted as the overall revenue channel.[15]

Using a similar testing suite as described in the replication section, I find strong evidence to support the presence of heteroskedasticity and C-S dependence in the expanded dataset. In addition, using the heteroskedasticity robust version of the test, I find no evidence of first order serial correlation using a common autoregressive parameter. I repeated the test several times, each time increasing the number of lags in the residuals up to twelve lag lengths. Individual t-tests of the coefficients on the lagged residuals indicate that lags 2, 4, 6, 7 and 8 are commonly significant at the 95% level of confidence. Joint tests of significance on all of the coefficients of the lagged residuals are statistically insignificant up to the inclusion of five lags of the residuals. When including lags of the residuals from 6 to 12, however, the joint tests indicate that at least one coefficient is statistically different from zero.

These results suggest that a higher order of serial correlation is present with the joint tests suggesting a lag of at least six. With the annual data used in the anlysis, such a long lag could be induced by the behavior of the industry sales variable or the macro-factor control variables (oil and

---

[14]The motivation for dropping the industry dummy variables is rooted in the statistical insignificance of these variables for all investment equation regressions in the replication section. Although not reported, I find the same result if I include the dummies for all of the FGLS regressions in Table 4.3.

[15]In Campa and Goldberg (1999), the authors treat this coefficient in the same manner.

the interest rate) over business cycle. Also, it could be that this test does not perform properly in the presence of C-S dependence, but I am not aware of any alternative test that is robust to its presence. In addition, I run the test on each industry individually with only one lag of the residuals. Those results suggest that two of the nineteen industries (leather products and stone, clay and glass products) do show evidence of a panel-specific $AR(1)$ process in the errors. Given the evidence for the presence of serial correlation at a higher order, I am faced with a quandry when using the FGLS and PCSE estimation methods. The question becomes one of whether to treat the serial correlation at all, because these methods assume a first order autoregressive process.[16]

In the initial analysis I use FGLS estimation of Equation (4.2) on the pooled sample of all U.S. manufacturing industries from 1974-2005. Since only two of the industries show evidence of panel-specific, first order serial correlation and no evidence of common, first order serial correlation; I choose to ignore treatment of this malady.[17] The results, which are presented in Table 4.3, are robust to the presence of heteroskedasticity and C-S dependence, only. The results presented in column (1) use the permanent component of the exchange rate (real value of the dollar), as determined from a B-N decomposition, and the nominal 10-year T-note as the interest rate from the expanded dataset; as a result, they are the most comparable to Campa and Goldberg (1999). Although the estimation approach taken here is quite different (placing priority on correcting for different violations to i.i.d. errors), the imported input series has been updated to reflect the most current input-output matrix, and the timeframe has been extended, the results in column (1) are remarkably similar to those of Campa and Goldberg. As in their results, the revenue channel is the only exchange rate channel that is significantly different from zero, indicating that the primary effect of the exchange rate upon investment for the U.S. manufacturing sector is largely dependent upon export share. The coefficient on sales is positive, statistically significant, and of the same order of magnitude as that of both the benchmark and previous investment studies.

In line with the investment literature, I also re-estimate the investment function with permanent exchange rates, using real values for the T-note and compare them with results using nominal and real values of the average annual yield on Aaa-rated, long-term corporate debt. These esti-

---

[16] In the appendix, I provide several sensitivity tests showing the results for different assumptions about serial correlation.

[17] Results for FLGS estimations that correct for a panel-specific and a common $AR(1)$ coefficient are presented in the appendix as Table 4.14 and Table 4.15, respectively. There is practically no difference between the results that assume no autocorrelation and those that assume a common $AR(1)$ coefficient. The results for the panel-specific $AR(1)$ correction are also similar, but display much higher levels of significance for many of the variables. The higher levels of significance associated with the panel-specific $AR(1)$ correction support the findings of Beck and Katz (1995).

Table 4.3. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Comparison between Nominal and Real Interest Rates, and between Permanent and Actual Exchange Rates. No Adjustment for Autocorrelation.

	Permanent component of exchange rate, $\hat{e}$				Actual exchange rate, e			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.00939**	0.00843**	0.00764*	0.00778**	0.00856*	0.00799*	0.00721*	0.00763*
	(2.03)	(2.04)	(1.82)	(2.04)	(1.90)	(1.86)	(1.71)	(1.92)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.214	-0.116	-0.188	-0.0157	-0.0123	0.0652	-0.00571	0.165
	(-1.07)	(-0.60)	(-1.02)	(-0.09)	(-0.05)	(0.28)	(-0.03)	(0.74)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-3.806***	-3.821***	-3.875***	-3.821***	-4.885***	-4.829***	-4.982***	-4.826***
	(-2.68)	(-2.70)	(-2.74)	(-2.71)	(-2.79)	(-2.75)	(-2.84)	(-2.76)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	3.213	2.913	3.463	2.573	-1.188	-1.359	-0.792	-1.623
	(1.02)	(0.94)	(1.13)	(0.85)	(-0.31)	(-0.36)	(-0.21)	(-0.44)
Δy^i_{t-1}	0.378***	0.400***	0.386***	0.404***	0.376***	0.389***	0.381***	0.396***
	(9.96)	(11.13)	(10.99)	(11.65)	(10.15)	(10.78)	(10.96)	(11.40)
Δoil_{t-1}	-0.0266	-0.0277	-0.0189	-0.0385**	-0.0394*	-0.0355*	-0.0325	-0.0423**
	(-1.10)	(-1.56)	(-0.87)	(-2.38)	(-1.67)	(-1.93)	(-1.49)	(-2.52)
Δr_{t-1}								
T-note	0.00245				0.00266			
	(0.48)				(0.54)			
real T-note		-0.00584				-0.00420		
		(-1.40)				(-0.98)		
Aaa			-0.00415				-0.00228	
			(-0.76)				(-0.43)	
real Aaa				-0.0118***				-0.00914**
				(-2.96)				(-2.17)
N	570	570	570	570	570	570	570	570

Notes: Statistics robust to heteroskedasticity and cross-sectional dependence; z statistics in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e and $\hat{e}$ are the real value of the dollar and its permanent component, respectively.

mates, which are presented in columns (2)-(4), indicate that the revenue channel and the accelerator effect are stable with respect to the choice of the interest rate. The most striking results, however, are found in column (4), when the real Aaa interest rate is used. Of the four options tested, the coefficient on the real Aaa rate is the only one that is statistically different from zero (albeit with very little economic relevance). Added to this, by including the real Aaa rate, the coefficient on the real price of oil variable also becomes statistically significant. As I repeatedly found in the replication section, this coefficent is negative, which what is expected from a proxy for the price of other inputs. When looked at as a whole, the results in column (4) are not that different from the results for all industries in the benchmark study.

While still in the overconfident mode of FGLS analysis, however, I use this framework to test the sensitivity of these results to the choice of exchange rate in an attempt to reconcile the differences between the results of the benchmark study and those of Landon and Smith (2007), Bahmani-Oskooee and Hajilee (2010), and Blecker (2007). Landon and Smith (2007) and Bahmani-Oskooee and Hajilee (2010) found that short run changes in the exchange rate had a significant effect on investment, while long run changes did not, and Blecker found evidence of a role for the exchange rate to affect investment via the channel of financial constraints. Using the permanent component of the exchange rate in this analysis eliminates the short-run changes, which are also most likely to affect the flow of investment (as opposed to the desired capital stock), such as the traditional proxies for financial constraints (cash flow or profits). Although I am unable to construct and control for industry level equivalents to those traditional proxies, I can test how changes in the actual exchange rate index affect the results in the Campa and Goldberg framework.

In columns (5)-(8) of Table 4.3, I repeat the previous estimations, but with the actual exchange rate index used in the calculation of the exchange rate channels. The main difference in the control variables is that the price of oil variable is now statistically significant for the regressions using the nominal and real T-note as the interest rate. Again, the channel weighted by export share is the only exchange rate coefficient that is statistically significant. These coefficients remain negative and highly significant, but the magnitudes are generally larger than the estimates obtained from using the permanent component of the exchange rate. Furthermore, there is an abrupt change from positive to negative values for the cost channel coefficients that arises when changing the measure of the exchange rate variable. This change could provide a hint towards the role that short-run changes in the exchange rate affect investment.

This particular model tries to delineate between the different channels for the exchange rate to affect the desired long run capital stock, which is one aspect of the choice to use the permanent component of the exchange rate changes in the analysis. The clear switch in signs for the cost channel could indicate that short-run changes in the exchange rate are likely to affect investment through the revenue channel, so much so, that they tend to dominate any long-run effect on the cost side. From a financial constraints perspective, this possibility could suggest that the short-run effect of changes in the exchange rate could have an influential role on investment through the revenue generation side of cash flow or profits. Moreover, I showed in the previous section on replication, that the results of this model are highly sensitive to the choice of method for determining the permanent component of the exchange rate. Taken together, these issues suggest that using the permanent component of the real value of the dollar as the exchange rate variable may not reflect the total effect of the exchange rate on investment. I, therefore, choose to use actual changes in the real value of the dollar for all additional estimates.

Table 4.4. Sample Splits by Markup and Import Share

	High markup		Low markup	
High Import Share	SIC 35	Industrial machinery	SIC 23	Apparel
	SIC 36	Electronics	SIC 25	Furniture
	SIC 38	Instruments	SIC 31	Leather
	SIC 39	Other mfg.	SIC 33	Primary metals
			SIC 37	Transportation equipment
Low Import Share	SIC 26	Paper	SIC 20	Food
	SIC 27	Printing	SIC 22	Textiles
	SIC 28	Chemicals	SIC 24	Lumber
	SIC 30	Rubber	SIC 29	Petroleum and coal
	SIC 32	Stone, clay and glass	SIC 34	Fabricated metals

The final analysis using FGLS provides another opportunity to test the sensitivity of the results from Campa and Goldberg (1999) to that of my extended data. One of the major conclusions of Campa and Goldberg is that the sensitivity of investment to changes in the exchange rate is dependent upon the competitive structure of the different industries. The authors use the industry markup as the indicator for the degree of competition within each industry. The industries with lower markups are likely to face greater competitive pricing pressure; thus, they are more likely to be affected by changes in the exchange rate. To investigate this assertion, Campa and Goldberg split their sample into low- and high-markup industries. If an industry's average markup is less than the median of the average markups for all industries, then the industry is classified as low-markup.

According to the data presented in Figure 3.2, the most striking change to the measures of industry exposure is found in the dramatic rise in the share of imported final goods in domestic consumption. As a result, one might expect that the increased competition from imported final goods would have an effect on the investment and exchange rate linkages within the U.S. manufacturing industries. In order to investigate this possibility, I also split the sample into two sub-samples based upon import penetration, m_j^i, which is used as an indicator for the relative degree of competition with imported final goods faced by each industry. I create the sample splits in the same manner as that of the markup. In Table 4.4, I report the manufacturing industries which fall under each category of high- or low-markup and high- or low-import penetration. The ten industries that are classified as low-markup in the extended dataset are also classified as such in Campa and Goldberg (1999). The only difference is that SIC 26, paper and allied products is classified here as a high-markup industry, due to its consistently rising markup since 1993.

Table 4.5. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Sample Splits by Markup and Import Competition. No Adjustment for Autocorrelation.

	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00763*	0.0188*	0.000820	0.0240*	0.00104
	(1.92)	(1.66)	(0.10)	(1.85)	(0.14)
$(\tilde{\kappa}_{t-1}^i)^{-1}\Delta e_{t-1}$	0.165	-0.973	-0.0446	-0.483	0.864*
	(0.74)	(-1.34)	(-0.11)	(-0.64)	(1.78)
$\chi_{t-1}^i(\tilde{\kappa}_{t-1}^i)^{-1}\Delta e_{t-1}$	-4.826***	-7.523*	0.661	-6.355***	-4.931
	(-2.76)	(-1.94)	(0.15)	(-2.62)	(-0.93)
$\alpha_{t-1}^i(\tilde{\kappa}_{t-1}^i)^{-1}\Delta e_{t-1}$	-1.623	12.01	-5.875	2.424	-11.40
	(-0.44)	(1.13)	(-1.10)	(0.35)	(-1.59)
Δy_{t-1}^i	0.396***	0.166**	0.484***	0.193**	0.327***
	(11.40)	(2.26)	(4.56)	(2.33)	(3.32)
Δoil_{t-1}	-0.0423**	0.0147	-0.0550	-0.0246	-0.0307
	(-2.52)	(0.30)	(-1.61)	(-0.44)	(-0.96)
Δr_{t-1}	-0.00914**	0.00145	-0.0114	0.00664	-0.0133*
	(-2.17)	(0.12)	(-1.36)	(0.49)	(-1.67)
N	570	270	300	270	300

Notes: Statistics robust to heteroskedasticity and cross-sectional dependence; z statistics in parentheses; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$; e is the real value of the dollar.

In Table 4.5, I present the estimation results for the different sub-samples using the actual changes in the exchange rate and the real Aaa interest rate.[18] Once again, I assume no first order correlation and present results that are robust to heteroskedasticity and C-S dependence, only.[19] Column (1) presents the results for all industries, and Columns (2) and (3) show the results of splitting the sample into sub-samples determined by relatively high and low markups. These results indicate that the cost channel ($\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$) does not have a significant impact on investment in either delineation of competition as measured by price-over-cost markup. In fact, for the low markup industries the only statistically significant coefficient is that of industry sales. I do find, however, that the coefficient on the revenue channel ($\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$) is statistically significant for the high markup industries, and may even indicate a stronger exchange rate effect for these industries relative to U.S. manufacturing as a whole. In addition, the distinct changes in the value for the accelerator effect present an interesting possibility. For the high markup firms in Column (2) the effect of industry sales on investment is weaker than that for all industries; while, for the low markup firms in Column (3) the accelerator effect is stronger. In the investment function literature, the accelerator effect is typically one of the most stable results. It is interesting that by including exchange rates in this model of investment, I find changes in the magnitude of its effect based upon the level of competition faced by a subsample of industries.

The results of splitting the sample into high and low import penetration are found in Columns (4) and (5), respectively. For those industries with low import penetration, the coefficient on industry sales is statistically significant, and its magnitude is relatively similar to that of all industries in the full sample. The only significant coefficient for an exchange rate interaction is that of $(\tilde{\kappa}^i_{t-1})^{-1}\Delta\hat{e}_{t-1}$, which according to the theoretical model measures the difference between the domestic price and the domestic markup exchange rate elasticities. The fact that this coefficient is positive ($\eta_{p,e} > \eta_{\kappa,e}$), supports the theoretical assertion that domestic manufacturing industries facing relatively less import competition have greater pricing power and would be able to pass through exchange rate changes in their prices without adjusting their markups to a significant degree. There is no additional evidence, however, of a role for the exchange rate to affect investment

[18]The results for regressions using the same variables as the benchmark study (permanent component of the exchange rate and the nominal T-note) provide qualitatively similar results with regards to statistical significance. Because I am also interested in the inclusion of short-term changes in the exchange rate and a real measure of the interest rate, I only present results using actual changes in the exchange rate and the real Aaa interest rate.

[19]Results for FGLS estimations that correct for a panel-specific and a common $AR(1)$ coefficient are presented in the appendix as Table 4.16 and Table 4.17. Again, there is practically no difference between the results that assume no autocorrelation and those that assume a common $AR(1)$ coefficient, and the results for the panel-specific $AR(1)$ correction are similar but with much higher levels of significance for many of the explanatory variables.

through either the revenue or the cost channels. In contrast, for the industries facing a higher level of import competition, one finds that the revenue channel is statistically significant and stronger than that for the full sample. In addition, the accelerator effect is considerably weaker. This result suggests that by including the effect of the exchange rate on investment, the traditional accelerator effect of industry sales is dampened. The slack, then, is taken up by the impact of the exchange rate on exports and domestic competition with imports through the revenue channel.

Table 4.6. OLS with PCSE: Sample Splits by Markup and Import Competition. No Adjustment for Autocorrelation.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00749	0.0156	0.00320	0.0111	0.00388
	(0.55)	(1.00)	(0.23)	(0.66)	(0.33)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.183	-0.206	-0.236	-0.194	0.0870
	(-0.21)	(-0.18)	(-0.27)	(-0.16)	(0.10)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-6.633*	-10.51*	-6.835	-8.641*	-2.973
	(-1.65)	(-1.79)	(-0.79)	(-1.90)	(-0.36)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	1.558	7.507	2.106	4.029	-4.024
	(0.16)	(0.46)	(0.18)	(0.37)	(-0.34)
Δy^i_{t-1}	0.414***	0.318***	0.562***	0.357***	0.549***
	(3.39)	(2.59)	(2.92)	(2.64)	(3.35)
Δoil_{t-1}	-0.0650	-0.0500	-0.0761	-0.0805	-0.0522
	(-1.12)	(-0.76)	(-1.30)	(-1.12)	(-1.03)
Δr_{t-1}	-0.00520	-0.0000619	-0.0108	-0.000582	-0.0111
	(-0.37)	(-0.00)	(-0.75)	(-0.03)	(-0.90)
N	570	270	300	270	300
R^2	0.097	0.096	0.105	0.093	0.113
RMSE	0.140	0.132	0.147	0.155	0.126
SSR	11.027	4.561	6.367	6.341	4.626

Notes: Statistics robust to heteroskedasticity and cross-sectional dependence; z statistics in parentheses; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; e is the real value of the dollar.

Recall, any conclusions made thus far should be treated with caution due to the likelihood of over-confident standard errors from the FGLS estimation. In Table 4.6, I present the results for splitting the sample by markups and import competition using estimation by pooled OLS with PCSE. Again, I choose to ignore any correction for first order serial correlation, so the results are robust to heteroskedasticity and C-S dependence, only.[20] The results from the PCSE estimations

[20]Results for PCSE estimations that correct for a panel-specific and a common $AR(1)$ coefficient are presented in the appendix as Table 4.18 and Table 4.19, respectively. The main difference in the results from using the common

support the findings of Beck and Katz (1995), who note the bias in standard errors from using FGLS. It is obvious from the results for the full sample presented in column (1) that the PCSE method yields more conservative estimates of statistical significance than FGLS. By using PCSE, the intercept and the coefficients on oil and the interest rate are no longer statistically significant. The accelerator effect, however, retains its statistical significance at the 1% level, and its magnitude is similar to that of the FGLS results. In addition, the coefficient on the revenue channel retains the expected negative sign and has a similar magnitude to its FGLS result; albeit, the level of significance is reduced to 10%.

Even with the more conservative estimates from PCSE estimation, the results for the coefficients on the revenue channel and industry sales retain the same pattern displayed from FGLS estimation in regard to the sample splits. Again, I find that investment in the high markup industries is sensitive to the exchange rate through the revenue channel and that the accelerator effect is dampened for these industries. The industries with relatively lower markups, on the other hand, display no evidence of sensitivity to the exchange rate, while the accelerator effect is stronger for these industries, relative to the full sample. The results for the samples that are split by degree of import competition also follow a similar pattern to the FGLS regressions. Those industries facing a higher level of competition with imports in the domestic final goods market show a statistically significant investment sensitivity to the exchange rate through the revenue channel. The magnitude of the accelerator affect for these industries is also smaller than that of the full sample. Those industries facing a lower level of import competition show no evidence of a significant effect of the exchange rate on investment; however, the magnitude of the sales accelerator appears to be greater than for the full sample.

As noted above, there is some evidence supporting the presence of higher order serial correlation, but I have been unable to address it in either the FLGS or PCSE methods. Table 4.7 presents the results of pooled OLS estimation with DKSE using the modified Bartlett kernel with a bandwidth of seven. The plug-in estimator for the lag length,[21] as developed in Hoechle (2007), suggests a lag of three when the time component is thirty years, but as noted previously, this selection criterion is often too small. Since I find evidence of a minimum of six for the order of the autoregressive nature of the errors, I choose that value as the lag in an attempt to be nearest to the

---

$AR(1)$ adjustment is that the coefficient for the revenue channel is no longer significant at 10%. The results from using the panel-specific $AR(1)$ adjustment are again more optimistic in terms of significance levels, but the overall conclusions remain the same.

[21] For the Bartlett kernel, the bandwidth is the lag length plus one

Table 4.7. OLS with DKSE: Sample Splits by Markup and Import Competition. Robust to Sixth Order Autocorrelation.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00749	0.0156	0.00320	0.0111	0.00388
	(0.56)	(1.08)	(0.27)	(0.61)	(0.36)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.183	-0.206	-0.236	-0.194	0.0870
	(-0.44)	(-0.40)	(-0.40)	(-0.28)	(0.21)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-6.633***	-10.51***	-6.835	-8.641**	-2.973
	(-3.01)	(-4.79)	(-1.05)	(-3.02)	(-0.46)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	1.558	7.507	2.106	4.029	-4.024
	(0.32)	(0.95)	(0.23)	(0.70)	(-0.68)
Δy^i_{t-1}	0.414***	0.318**	0.562***	0.357***	0.549**
	(3.69)	(2.57)	(4.17)	(3.76)	(2.35)
Δoil_{t-1}	-0.0650*	-0.0500	-0.0761	-0.0805	-0.0522
	(-1.74)	(-1.70)	(-1.60)	(-1.50)	(-1.72)
Δr_{t-1}	-0.00520	-0.0000619	-0.0108	-0.000582	-0.0111
	(-0.56)	(-0.01)	(-1.56)	(-0.06)	(-1.24)
N	570	270	300	270	300
R^2	0.097	0.096	0.105	0.093	0.113
RMSE	0.140	0.132	0.147	0.155	0.126

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence and up to $AR(6)$; t statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e is the real value of the dollar.

automatic selection criterion yet representative of the actual error process found from the data.[22] For comparison, I present the results for the sample as a whole and for splitting the sample by markups and import competition.

First, one should note that the coefficient estimates using the DKSE method presented in Table 4.7 are the same as those presented in Table 4.6, which displays the results from the PCSE method with no correction for autocorrelation. The PCSE method only uses a Prais-Winsten estimation to account for serial correlation. Without such a correction, the results derive from an OLS regression with standard errors corrected for heteroskedasticity and C-S dependence. The OLS results from the DKSE method presented in Table 4.7, however, display t-statistics that are robust

[22]Results for DKSE estimations using the automatic lag length of three and a lag of zero (which does not correct for autocorrelation) are presented in the appendix as Table 4.20 and Table 4.21, respectively. The overall conclusions are relatively insensitive to the autocorrelation factor. The main difference is that with no adjustment for autocorrelation, the coefficient for the revenue channel is only significant at 10%. In addition, the oil coefficient is insignificant for both sensitivity tests.

to heteroskedasticity, C-S dependence, and up to 6th order autocorrelation. With DKSE, all of the estimated coefficients for the accelerator effect remain statistically different than zero with 95% confidence, and the coefficient on the price of oil is once again statistically significant for the full sample with 90% confidence. As in the PCSE method, the only statistically significant exchange rate coefficients are those of the revenue channel for the full sample and the subsamples for the industries with relatively higher markups and facing relatively higher import competition. With DKSE all three of these coefficients are statistically different than zero with 95% confidence.

Table 4.8. FEGMM with DKSE: Sample Splits by Markup and Import Competition. Robust to Sixth Order Autocorrelation. Tests of Interest Rate Endogeneity.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00562	0.0127	0.00226	0.00938	0.00201
	(0.45)	(0.94)	(0.18)	(0.54)	(0.18)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.961	-1.612	-0.544	-0.835	-1.001
	(-1.38)	(-1.64)	(-0.86)	(-1.10)	(-1.21)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-7.569***	-13.220***	-6.995	-8.796***	-5.148
	(-3.42)	(-4.05)	(-1.00)	(-3.45)	(-0.62)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	6.131	18.017	3.607	6.962	4.348
	(0.94)	(1.44)	(0.41)	(1.33)	(0.37)
Δy^i_{t-1}	0.385**	0.300*	0.534***	0.348***	0.462*
	(2.60)	(1.99)	(3.43)	(2.93)	(1.74)
Δoil_{t-1}	-0.0643	-0.0483	-0.0760	-0.0787	-0.0514
	(-1.61)	(-1.45)	(-1.54)	(-1.43)	(-1.52)
Δr_{t-1}	0.0251	0.0494	0.00210	0.0231	0.0276
	(0.69)	(1.30)	(0.06)	(0.52)	(0.86)
Tests of identification and endogeneity					
Underident. Test[a]	3.581*	3.639*	3.450*	3.565*	3.599*
p-value	0.0584	0.0564	0.0632	0.0590	0.0578
Endogeneity Test[b]	1.058	2.008	0.202	0.506	1.480
p-value	0.3037	0.1565	0.6530	0.4769	0.2238
N	570	270	300	270	300
R^2	0.059	-0.021	0.099	0.073	0.038
RMSE	0.143	0.140	0.148	0.157	0.131

Notes: Statistics, tests of identification, and tests of endogeneity are robust to heteroskedasticity, cross-sectional dependence and up to $AR(6)$; t statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[a] Kleibergen-Paap rk LM statistic; H_o : equation is underidentified.

[b] C statistic; $H_o : \Delta r_{t-1}$ actually can be treated as exogenous.

Thus far, I have presented results that attempt to tackle the "unholy trinity" of violations to OLS. In doing so, I have ignored any bias that may have been induced by treating the markup and the interest rate as exogenous. Using the *ivreg2* routine, however, I can perform a FEGMM estimation which treats the interest rate as endogenous and uses DKSE to correct for the entire clover leaf of OLS violations. The results from such an estimation are presented in Table 4.8, where the single excluded instrument is the first lag of the change in the nominal T-note. Again, I present results for the full sample and subsamples divided by markup and import competition.

In this framework, identification issues begin to arise in regards to IV/GMM estimation. In addition, these issues seem to increase with the number of lags used to correct for autocorrelation. I choose the first lag of the change in the nominal T-note as the sole member of the excluded instrument set, because that is the only combination[23] that allowed for a rejection of the under-identification test with at least 90% confidence. With a single endogenous regressor and a single excluded instrument, the estimated equation is exactly identified, which pares the suite of tests for identification and endogeneity from those presented in the replication section. The results of the tests are presented in the lower section of Table 4.8. The results of the underidentification test are consistent across all subsample splits. Because the estimated equation is not overidentified, I am unable to test the exogeneity of the exchange rate channels, which could provide clues as to whether the markup can be treated econometrically as exogenous. I can, however, perform an endogeneity test on the interest rate. The results of this test suggest that the interest rate can be treated as exogenous for the full sample and all sample splits, which lends support for my use of OLS. In addition, instrumenting the interest rate with the FEGMM/DKSE method yields estimated coefficients that maintain a similar pattern in terms of magnitude and statistical significance to that of the OLS with DKSE method.

The results presented thus far provide an interesting contrast to the results of Campa and Goldberg (1999), whose findings emphasized the amplified effect of the exchange rate on the industries that face a relatively higher level of competition as measured by a low markup. My results, in contrast, suggest that the industries that face relatively lower competition (as indicated by higher markups) are the industries in which investment is sensitive to the exchange rate. Due to the extended time period of the data and the updated input-output matrix, the results presented here

[23] I tried multiple combinations of single and multiple lags; levels and changes; nominal and real; interest and exchange rates. The first lag of the nominal T-note is the only one, which passed muster with a 10% level of significance.

could reflect an evolution in the structure of U.S. manufacturing from the time period investigated by Campa and Goldberg. The change could reflect a shift in U.S. manufacturing towards the production of high-markup goods that are competitive in the global market and away from low-markup goods that have difficulty competing with goods from low-labor cost countries. Given this possibility, the driving factor behind the exchange rate effect of the revenue channel on investment likely is due to the export channel. On the other hand, I also find that the industries that face relatively greater competition from imported final goods (as indicated by the higher level of import penetration) are the industries with exchange rate sensitive investment. In this respect, the driving factor behind the exchange rate effect of the revenue channel on investment likely is due to the domestic channel.

As noted earlier, the construction of the empirical model prohibits a clear delineation between the two aspects that make up the revenue channel: the domestic channel, whereby industries are competing with imported final goods in the domestic market and the export channel, whereby the industries' exports are competing in the foreign market. In the next analysis, I attempt to address this shortcoming by modifying the original model to include a term for the interaction between the real exchange rate and the measure of import penetration, m. By including this term, I weaken the link between the estimation equation and the original theoretical model; so I take advantage of the opportunity to investigate what also happens if the markup variable is removed from all exchange rate interaction terms. An additional rationale for removing the markup variable is to remove any simultaneity basis that arose from treating it as an exogenous variable. As a result of these changes, the new econometric specification is as follows:

$$\begin{aligned} \Delta I_t^i = \beta_0 &+ \left(\beta_1 m_{t-1}^i + \beta_2 \chi_{t-1}^i + \beta_3 \alpha_{t-1}^i\right) \Delta e_{t-1} \\ &+ \beta_4 \Delta y_{t-1}^i + \beta_5 \Delta oil_{t-1} + \beta_6 \Delta r_{t-1} + \mu_t^i \end{aligned} \tag{4.3}$$

where the domestic channel effect, β_1, is estimated by the interaction between import share and the real exchange rate and the markup is removed from all three exchange rate channels. The results for estimating Equation (4.3) by OLS with DKSE are presented in Table 4.9.

After modifying the estimation equation, the results for the full sample, presented in column (1), are similar to those of the previous regressions. The estimated coefficients for industry sales and the price of oil are very close to previous estimates in terms of both magnitude and statistical significance. Under the new specification, the only exchange rate channel that is statistically

Table 4.9. OLS with DKSE: Modified Domestic Channel.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00699	0.0153	0.00226	0.0107	0.00368
	(0.51)	(1.05)	(0.18)	(0.58)	(0.35)
$m^i_{t-1}\Delta e_{t-1}$	-0.986	1.134	-1.524*	-1.673	-4.694
	(-1.20)	(1.15)	(-1.86)	(-1.51)	(-1.71)
$\chi^i_{t-1}\Delta e_{t-1}$	-3.711**	-6.875***	-1.905	-5.623**	-1.451
	(-2.49)	(-4.67)	(-0.44)	(-3.30)	(-0.32)
$\alpha^i_{t-1}\Delta e_{t-1}$	1.187	1.701	0.766	5.414*	2.766
	(0.54)	(0.49)	(0.23)	(1.87)	(0.46)
Δy^i_{t-1}	0.424***	0.321**	0.579***	0.364***	0.553**
	(3.58)	(2.50)	(4.43)	(3.67)	(2.43)
Δoil_{t-1}	-0.0668*	-0.0536*	-0.0747	-0.0844	-0.0516
	(-1.91)	(-1.94)	(-1.65)	(-1.76)	(-1.78)
Δr_{t-1}	-0.00682	-0.000774	-0.0123	-0.00184	-0.0118
	(-0.66)	(-0.06)	(-1.47)	(-0.15)	(-1.30)
N	570	270	300	270	300
R^2	0.098	0.097	0.108	0.097	0.113
RMSE	0.140	0.132	0.147	0.155	0.126

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence and up to $AR(6)$; t statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

different from zero is that of the export channel. By controlling for both the weight of imported, manufacturing inputs used in production and the weight of competing imports in the domestic market for final goods; this result suggests that total U.S. manufacturing investment is sensitive to changes in the real exchange rate by means of the effect of these changes on export prices. Moreover, these results provide additional evidence that the real value of the dollar has a large and significant negative effect on U.S. manufacturing investment, overall.

The results for the high markup industries are presented in column (2) and support my assertion that the export channel is the driving factor for the effect of the exchange rate on investment for these industries. Again, I find the pattern whereby the accelerator effect is dampened and the export channel is amplified for the high markup industries when compared to the full sample. The results in column (3) of the new specification suggest that investment in the low markup industries may also be sensitive to the value of the dollar. For these industries, however, it is the domestic channel through which the exchange rate affects investment. Of all the results presented thus far, this is the first time that I find evidence of exchange rate sensitive investment for the low markup industries; although the coefficient is only significant at 10%. For these industries, a declining dollar would increase the prices of competing imports and encourage additional investment by U.S. manufacturers. The incremental increase in investment for the low markup industries due to changes in the value of the dollar, however, appears to be significantly less than that for the high markup industries. I also find evidence that the accelerator effect is amplified for the low markup industries, which suggests that the effect of sales growth on investment is more important for those industries facing greater competitive pricing pressures. Taken together, the results for the subsamples split by markup rate support my hypothesis about the evolution of the structure of U.S. manufacturing towards the production of high markup goods that compete globally, and away from low markup goods that face greater pricing pressure from imported goods.

In columns (4) and (5) of Table 4.9, I report the estimation results using OLS with DKSE for the samples split by level of import competition. The industries that face relatively less competition from imported final goods show no evidence of an effect of the real exchange rate on investment. The sales accelerator for these industries, however, tends to be amplified in comparison to all U.S. manufacturing. The results for the industries facing relatively greater import competition are quite interesting. First, I find evidence that it is once again through the export channel that the value of the dollar negatively affects investment. This result is contrary to my expectation that the domestic channel is the driving factor of the revenue effect on investment for those industries that face greater competition from imports. For these industries, I also find evidence of a role for the exchange rate to affect investment through its effect on the cost of imported inputs. Of the results presented thus far, this is the first time that I find supporting evidence for the role of the cost channel; although, the coefficient is only significant at 10%. Interestingly, the magnitude of the cost channel is such that it may completely offset the effect of the exchange rate ocurring through the export channel. By including the exchange rate, I again find that the sales accelerator is dampened for the industries facing greater competition from imports.

Taken together, the results for the samples split by import competition paint a different picture of the structure of U.S. manufacturing than those for the samples split by markup rates. For the industries that face relatively lesser import competition, the most important factor in the investment decision is sales growth, and it does not seem to matter if these sales are domestic or exports. For the industries facing greater competition from imports, however, it seems as if the investment decision is sensitive to changes in the exchange rate. In this case, total sales growth has less of an impact on investment, and the share of export revenue in these sales becomes an important factor in the investment decision. Although these industries may be facing greater pressure from competing imports in the domestic market, they are also competing on the global market through their exported goods;,and it is the effect of the value of the dollar on these export revenues that mostly influences the investment decision. In addition, it is quite possible that the greater pricing pressure from competing imports in the domestic market makes the cost management aspect of profitibility more important for investment. Under this scenario, these industries may be more likely to outsource the production of intermediate manufactured goods in order to reduce costs.

In the analyses presented so far in the extension section, the results for industry level investment that are most robust to varying specifications and estimation methods are the positive accelerator effect of industry sales and a negative effect of actual changes in the real exchange rate through the export channel for all U.S. manufacturing industries and for subsamples with higher markups or greater import penetration. I find very little evidence of an exchange rate to investment linkage through the cost channel, which is a cornerstone of the results presented in Campa and Goldberg (1999). The lack of significant role for the exchange rate to effect investment through the cost channel is suprising given the steady rise in the imported input share for all industries as shown in Figure 1. One potential reason for this result is that manufacturing firms are able to manage their exchange rate exposure on the cost side through their global supply chains. Given the dominance of the U.S. dollar as an international transaction currency and the use of long-term supply contracts, firms may have a built-in hedge against currency effects on their imported, manufactured intermediate goods. Another potential reason is that the assumptions used to create the imported input share, α, are too heroic (recall the discussion in Chapter 3 of the need for caution with this series).

4.2.3 Industry Level Exchange Rates

Leaving aside the focus on imported inputs, I now use industry-specific exchange rate indexes in the next analyses to narrow in on the overall exchange rate effect on investment in U.S. manufacturing industries. Recall that the industry-specific total exchange rate is a weighted average that accounts for domestic competition with imports and foreign competition with exports for each industry at the two-digit SIC level. As a result, the econometric specification changes by replacing the interacted exchange rate terms for the revenue and cost channels with a single measure for the exchange rate. The new specification is

$$\Delta I_t^i = \beta_0 + \beta_1 \Delta e_{t-1}^i + \beta_2 \Delta y_{t-1}^i + \beta_3 \Delta oil_{t-1} + \beta_4 \Delta r_{t-1} + \mu_t^i \tag{4.4}$$

where Δe_{t-1}^i is the first lag of the log difference of the industry-specific total exchange rate. For comparison, I estimate Equation (4.4) by OLS with DKSE and a lag length of six.

Table 4.10. OLS with DKSE: Industry-specific, Total Trade Weighted Exchange Rates.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00927	0.0163	0.00503	0.0134	0.00529
	(0.70)	(1.16)	(0.39)	(0.74)	(0.51)
Δter_{t-1}^i	-0.508**	-0.523*	-0.481*	-0.659*	-0.338**
	(-2.34)	(-1.95)	(-2.22)	(-1.89)	(-2.71)
Δy_{t-1}^i	0.405***	0.308*	0.551***	0.332**	0.559**
	(3.38)	(2.19)	(4.19)	(3.03)	(2.49)
Δoil_{t-1}	-0.0576*	-0.0371	-0.0714	-0.0628	-0.0487
	(-1.76)	(-1.28)	(-1.63)	(-1.43)	(-1.77)
Δr_{t-1}	-0.00423	0.00153	-0.0101	0.00164	-0.0103
	(-0.44)	(0.12)	(-1.55)	(0.15)	(-1.26)
N	570	270	300	270	300
R^2	0.089	0.077	0.101	0.080	0.111
RMSE	0.140	0.133	0.147	0.156	0.125

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence and up to $AR(6)$; t statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results for the full sample and splits by markup and import competition are presented in Table 4.10.[24] The full sample results reported in Column (1) support the previous finding that the real value of the dollar has a significant negative effect on investment for U.S. manufacturing as a whole. In addition, the accelerator effect for the full sample is found to be positive, significant and of similar magnitude to the regressions that include the different exchange rate channels. Repeating these findings when using the industry-specific total exchange rates supports the conclusion that they are the most robust of the results found in the industry-level analysis.

[24]The results for heteroskedasticity and C-S dependence robust estimations using FLGS and PCSE methods are presented in the appendix as Table 4.22 and Table 4.23, respectively. The FGLS results are similar with the exception of an insignificant exchange rate coefficient for the low import competition sample. The PCSE results only yield a single significant exchange rate coefficient for the high import competition sample, and it is only at 10%

Because the log difference of the exchange rate now enters the estimation equation without any interaction with other variables, it is easy to compare the investment exchange rate elasticity to the investment sales growth elasticity and see that the magnitude of the effect of an appreciating or depreciating dollar on investment is on par with that of the traditional accelerator effect. In fact, the results for the full sample of U.S. manufacturing industries suggest that for a given level of real sales growth, a one percent depreciation in the real value of the dollar at the industry level would lead to a 0.5% increase in investment growth, *ceteris parabis.* At the same time, given a level of appreciation or depreciation of the real value of the dollar, a one percent increase in real sales growth would lead to a 0.4% increase in investment growth, *ceteris parabis.* In addition, by using industry-specific measures of the real exchange rate, I find evidence of a negative and significant effect of the real dollar on investment across all subsamples; although, only the coefficients for the entire sample and the lower import competition sample are significant at 5%. I also find that the pattern on the accelerator effect remains when controlling for the industry-specific exchange rate.

Table 4.11. OLS with DKSE: Industry-specific, Import Weighted Exchange Rates.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00835	0.0152	0.00417	0.0128	0.00417
	(0.64)	(1.09)	(0.34)	(0.72)	(0.41)
Δmer^i_{t-1}	-0.318	-0.378	-0.253	-0.525	-0.119
	(-1.68)	(-1.74)	(-1.44)	(-1.58)	(-1.16)
Δy^i_{t-1}	0.411***	0.305*	0.576***	0.321**	0.582**
	(3.28)	(2.12)	(4.48)	(2.72)	(2.52)
Δoil_{t-1}	-0.0549	-0.0327	-0.0690	-0.0556	-0.0472
	(-1.61)	(-1.09)	(-1.49)	(-1.21)	(-1.62)
Δr_{t-1}	-0.00750	-0.000645	-0.0140	0.000345	-0.0144
	(-0.72)	(-0.05)	(-1.83)	(0.03)	(-1.58)
N	570	270	300	270	300
R^2	0.080	0.070	0.092	0.075	0.103
RMSE	0.141	0.133	0.148	0.156	0.126

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence and up to $AR(6)$; t statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In the previous analyses that include the different exchange rate channels, I found evidence supporting the export share as the main driver for any linkage between the real exchange rate and investment and that the results differ depending on import penetration; as a result, I re-estimate Equation (4.4) using the import-weighted real exchange rate and again, using the export-weighted real exchange rate. These results are presented in Table 4.11 and Table 4.12, respectively. The estimates reported in Table 4.11 indicate that the industry-specific, import-weighted real exchange rate has no statistically significant effect on industry investment. This result holds for the full sample and both sets of subsamples; although, the sign on the exchange rate coefficient is consistently negative. The only statistically significant coefficient is that of the industry sales. In fact, the estimates for the accelerator effect are relatively unchanged from using the industry-specific total real exchange rate in terms of both statistical significance and magnitude. These findings lend additional supporting evidence for the export channel being the main conduit by which the exchange rate affects investment.

Table 4.12. OLS with DKSE: Industry-specific, Export Weighted Exchange Rates.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00927	0.0172	0.00427	0.0131	0.00565
	(0.69)	(1.21)	(0.33)	(0.71)	(0.54)
Δxer^i_{t-1}	-0.560**	-0.590*	-0.517**	-0.656**	-0.454**
	(-3.08)	(-2.09)	(-2.90)	(-2.41)	(-3.49)
Δy^i_{t-1}	0.412**	0.317*	0.552**	0.351**	0.545**
	(3.55)	(2.29)	(4.25)	(3.45)	(2.47)
Δoil_{t-1}	-0.0603*	-0.0438	-0.0710	-0.0706	-0.0488*
	(-1.93)	(-1.59)	(-1.62)	(-1.69)	(-1.84)
Δr_{t-1}	-0.00391	0.00152	-0.00949	-0.0000944	-0.00810
	(-0.45)	(0.12)	(-1.63)	(-0.01)	(-1.12)
N	570	270	300	270	300
R^2	0.094	0.081	0.107	0.078	0.121
RMSE	0.140	0.132	0.147	0.156	0.125

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence and up to $AR(6)$; t statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

I now turn to the estimates that result from using the industry-specific export-weighted real exchange rate, as reported in Table 4.12. Again, I find the same pattern for the accelerator effect as that found when using the total and import-weighted industry-specific real exchange rates, and once again, the magnitude of these estimated coefficients are relatively unchanged. In addition, by using the export-weighted real exchange rate, both the magnitude and statistical significance of the coefficients on the exchange rate changes are relatively unchanged from those using the total industry exchange rate for the full sample and across all subsamples. The fact that these coefficients display no statistical significance when using the import-weighted exchange rate and are relatively unchanged between the export-weighted and total industry exchange rate results, provides the strongest evidence yet that the real value of the dollar tends to affect investment decisions mainly through its impact on competitiveness in export markets.

4.3 Conclusion

This section begins with some general conclusions about my findings in regard to estimating the standard theoretical model of investment with exchange rate effects of Campa and Goldberg (1999) using industry level data. I highlight potential shortcomings of previous studies using this model, and pinpoint important differences that arise from using more recent data and improved econometric techniques compared with the benchmark study. I then discuss conclusions that result from modifying the traditional model in an effort to identify the overall effect of the exchange rate on investment in the U.S. manufacturing sector.

First, my results suggest that Campa and Goldberg (1999) may have placed priority on the wrong set of departures from OLS assumptions. By using recent advances in IV/GMM estimation techniques and diagnostics, I conclude that priority should be placed on addressing heteroskedasticity and cross-sectional dependence. In addition, I find that it is necessary to take much longer lags into account (rather than the one lag considered in the benchmark study) in controlling for the autoregressive nature of the errors. I also question whether treating the markup and the interest rate as endogenous is justified from a purely econometric standpoint.

Overall, I find very little evidence of an exchange rate to investment linkage through its effect on the price of imported intermediate goods, which is a cornerstone of the results presented in Campa and Goldberg (1999). The lack of significant role for the exchange rate to effect investment through the cost channel is quite suprising given the steady rise in the imported input share for most U.S. manufacturing industries. At the same time, extending the analysis from 1993 to 2005 ensures that the time period of investigation includes the start of the era of globalization and the accompanying explosion in international trade. As a result, any positive effects of an appreciating dollar on the cost of imported intermediaries may be outweighed by the negative effect that it has on competitiveness in export markets or with competing imports in the domestic market.

On the other hand, I find very robust evidence of a large and negative effect of an appreciating real value of the dollar on the investment decision through its impact on industry competitiveness in export markets. This finding is robust to multiple estimation techniques and alternative measures of the exchange rate. Using the full model of Campa and Goldberg (1999) that relies on interacting measures of external orientation with the broad, trade-weighted real value of the dollar, I find a range of estimates for the revenue channel of -3.711 to -7.569 for the full sample, most of which are significant at least at 5%.[25] In comparison, Campa and Goldberg (1999) estimate this effect at -6.218 for the U.S. manufacturing sector.

While using the full model of Campa and Goldberg (1999), I also find evidence that the effect of the exchange rate through the revenue channel is dependent on the type and degree of competition facing the industry. My results suggest that industries facing a higher degree of overall competition as indicated by a lower price over cost markup or those facing a lower degree of competition from imports as indicated by lower import penetration, do not alter their investment in response to a change in the real value of the dollar. In contrast, I find that industries facing a lower degree of overall competition or those facing a higher degree of competition from imports, show evidence of investment that is sensitive to changes in the real value of the dollar. These results differ from Campa and Goldberg (1999), who find a significant exchange rate effect on investment for the industries that face a relatively higher level of competition as measured by a low markup. Given the longer time period used in this analysis, the difference in results could reflect a shift in U.S. manufacturing towards the production of high-markup goods that are competitive in the global market and away from low-markup goods that have difficulty competing with goods from low-labor cost countries.

The most convincing evidence for an overall negative effect of the real exchange rate on investment occurs when modifying the traditional model of Campa and Goldberg (1999) to include industry-specific exchange rates of the type later developed by Goldberg (2004). By including these industry level exchange rates, I do away with the interaction terms between the exchange rate and the measures of external exposure. After including either the total-trade or export-weighted industry exchange rates, I consistently find evidence of a large, negative effect of the real exchange rate on investment. These elasticities range from -0.659 to -0.454 and are at least signficant at 10% across all sub-samples. In addition these estimates are similar in magnitude to the estimates

[25] The lone exception is the result for the most conservative estimate (PCSE), which is significant at 10%.

that are consistently found for the accelerator effect. In contrast, I find that including the import-weighted industry real exchange rate yields negative but insignificant coefficient estimates, which suggests that the effect of the exchange rate on investment is likely determined by its effect on industry competitiveness in export markets.

Overall, the results presented here suggest that the real value of the dollar does have an important effect on investment decisions in U.S. manufacturing industries and should be accounted for in any model of investment. The significant negative effect of the real value of the dollar found here is broadly in line with the findings of Blecker (2007) for the aggregate U.S. manufacturing sector. However, Blecker found that the exchange rate was usually significant in levels, indicating that it operated mainly by influencing financial or liquidity constraints. In contrast, the bulk of the evidence in this chapter suggests that the exchange rate affects U.S. manufacturing investment mainly through its impact on export market competitiveness and the effect of the latter on desired capital stocks, as postulated in the theoretical model of Campa and Goldberg (1999).

4.A Sensitivity Tests

Table 4.13. Replication of 3SLS: No Correction for Serial Correlation

	Benchmark	BN (IFS)	HP (IFS)	BN (Fed)	HP (Fed)
Investment (ΔI_t^i)					
$(\tilde{\kappa}_{t-1}^i)^{-1}\Delta\hat{e}_{t-1}$	0.337	-0.118	0.294	-0.145	-0.044
	(1.25)	(-0.43)	(0.36)	(-0.37)	(-0.05)
$\chi_{t-1}^i(\tilde{\kappa}_{t-1}^i)^{-1}\Delta\hat{e}_{t-1}$	-6.218*	-2.891	-0.346	-3.322	-0.536
	(1.79)	(-1.34)	(-0.06)	(-1.11)	(-0.07)
$\alpha_{t-1}^i(\tilde{\kappa}_{t-1}^i)^{-1}\Delta\hat{e}_{t-1}$	5.634	6.007*	-7.410	6.752	-7.951
	(1.28)	(1.76)	(-0.76)	(1.44)	(-0.62)
Δy_{t-1}^i	0.535**	0.796**	0.757**	0.570**	0.521**
	(5.75)	(4.86)	(4.66)	(4.06)	(3.79)
Δoil_{t-1}	0.052**	-0.133**	-0.117*	-0.157**	-0.123**
	(2.17)	(-2.17)	(-1.94)	(-2.50)	(-2.04)
Δr_{t-1}	-0.169**	0.020	0.019	0.027**	0.023*
	(-2.31)	(1.54)	(1.42)	(2.07)	(1.74)
Markup ($\Delta\tilde{\kappa}_t^i$)					
$\Delta\hat{e}_t$	-0.190**	0.036	0.170	0.078*	0.129
	(-2.09)	(1.05)	(1.40)	(1.69)	(0.93)
$\chi_t^i\Delta\hat{e}_t$	2.588**	0.253	0.024	0.263	-0.110
	(2.48)	(1.15)	(0.03)	(0.89)	(-0.13)
$\alpha_t^i\Delta\hat{e}_t$	-2.232	-1.279	-5.079*	-2.292**	-4.177
	(-1.64)	(-1.61)	(-1.78)	(-2.16)	(-1.23)
$m_t^i\Delta\hat{e}_t$	-0.033	0.373	1.445*	0.575*	1.359
	(-0.08)	(1.54)	(1.72)	(1.79)	(1.38)
Δy_t^i	0.184**	0.199**	0.195**	0.195**	0.187**
	(4.60)	(8.25)	(7.97)	(9.72)	(9.40)
N		320	340	360	360
Period		1978-93	1977-93	1976-93	1976-93

Notes: $*p < 0.10$, $**p < 0.05$; t statistics in parentheses; $\hat{e}$ is the permanent component of the real value of the dollar.

Table 4.16. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Sample Splits by Markup and Import Competition. Adjustment for Panel-specific $AR(1)$ Correlation.

	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.008**	0.024*	0.001	0.016	0.004
	(2.74)	(2.06)	(0.12)	(1.29)	(0.62)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	0.158	-0.628	0.125	-0.670	0.921**
	(0.97)	(-0.88)	(0.35)	(-0.95)	(2.05)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-6.173***	-9.256**	-4.281	-7.483***	-4.271
	(-3.42)	(-2.37)	(-1.05)	(-2.91)	(-0.77)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.257	12.47	-4.667	4.563	-11.16
	(-0.08)	(1.23)	(-0.96)	(0.71)	(-1.57)
Δy^i_{t-1}	0.484***	0.229***	0.596***	0.312***	0.417***
	(15.28)	(2.90)	(6.46)	(3.46)	(4.47)
Δoil_{t-1}	-0.0394***	0.0397	-0.0751***	0.0183	-0.0249
	(-3.42)	(0.92)	(-2.83)	(0.35)	(-0.86)
Δr_{t-1}	-0.00925***	0.00653	-0.0161**	-0.000717	-0.0115
	(-3.19)	(0.62)	(-2.50)	(-0.06)	(-1.61)
N	570	270	300	270	300

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence, and panel-specific $AR(1)$ correlation; z statistics in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e is the real value of the dollar.

Table 4.14. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Comparison between Nominal and Real Interest Rates, and between Permanent and Actual Exchange Rates. Adjustment for panel-specific $AR(1)$.

	Permanent component of exchange rate, $\hat{e}$				Actual exchange rate, e			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.00834**	0.00784***	0.00687**	0.00784***	0.00806**	0.00806**	0.00693**	0.00809***
	(2.34)	(2.58)	(2.23)	(2.94)	(2.19)	(2.30)	(2.08)	(2.74)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.201	-0.110	-0.161	-0.00916	-0.00219	0.0708	0.00427	0.158
	(-1.33)	(-0.77)	(-1.17)	(-0.07)	(-0.01)	(0.39)	(0.03)	(0.97)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-4.330***	-4.429***	-4.463***	-4.594***	-6.017***	-6.020***	-6.207***	-6.173***
	(-2.95)	(-3.04)	(-3.07)	(-3.24)	(-3.29)	(-3.28)	(-3.40)	(-3.42)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	3.443	2.970	3.444	2.827	0.226	-0.156	0.583	-0.257
	(1.35)	(1.21)	(1.40)	(1.20)	(0.07)	(-0.05)	(0.19)	(-0.08)
Δy^i_{t-1}	0.462***	0.491***	0.473***	0.499***	0.453***	0.472***	0.458***	0.484***
	(13.22)	(14.79)	(14.60)	(15.77)	(13.35)	(14.03)	(14.30)	(15.28)
Δoil_{t-1}	-0.0231	-0.0244**	-0.0157	-0.0365***	-0.0328*	-0.0311**	-0.0253*	-0.0394***
	(-1.39)	(-2.04)	(-1.10)	(-3.41)	(-1.91)	(-2.32)	(-1.66)	(-3.42)
Δr_{t-1}								
T-note	0.00140				0.000470			
	(0.39)				(0.13)			
real T-note		-0.00474*				-0.00434		
		(-1.70)				(-1.40)		
Aaa			-0.00513				-0.00491	
			(-1.37)				(-1.26)	
real Aaa				-0.0109***				-0.00925***
				(-4.12)				(-3.19)
N	570	570	570	570	570	570	570	570

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence, and panel-specific $AR(1)$ correlation; z statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e and $\hat{e}$ are the real value of the dollar and its permanent component, respectively.

Table 4.15. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Comparison between Nominal and Real Interest Rates, and between Permanent and Actual Exchange Rates. Adjustment for Common $AR(1)$.

	Permanent component of exchange rate, $\hat{e}$					Actual exchange rate, e		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.00938**	0.00845**	0.00766*	0.00788**	0.00857*	0.00801*	0.00726*	0.00774*
	(2.03)	(2.04)	(1.82)	(2.03)	(1.90)	(1.86)	(1.71)	(1.92)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.214	-0.115	-0.188	-0.0108	-0.0122	0.0665	-0.00549	0.172
	(-1.07)	(-0.60)	(-1.01)	(-0.06)	(-0.05)	(0.28)	(-0.02)	(0.77)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-3.813***	-3.808***	-3.865***	-3.757***	-4.879***	-4.818***	-4.957***	-4.763***
	(-2.69)	(-2.69)	(-2.73)	(-2.65)	(-2.78)	(-2.74)	(-2.82)	(-2.70)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	3.221	2.891	3.452	2.476	-1.197	-1.381	-0.828	-1.747
	(1.03)	(0.94)	(1.12)	(0.82)	(-0.32)	(-0.36)	(-0.22)	(-0.47)
Δy^i_{t-1}	0.379***	0.398***	0.385***	0.398***	0.374***	0.387***	0.378***	0.390***
	(9.99)	(11.09)	(10.98)	(11.42)	(10.06)	(10.69)	(10.79)	(11.12)
Δoil_{t-1}	-0.0266	-0.0279	-0.0189	-0.0393**	-0.0393*	-0.0355*	-0.0324	-0.0429**
	(-1.10)	(-1.57)	(-0.87)	(-2.42)	(-1.67)	(-1.93)	(-1.48)	(-2.56)
Δr_{t-1}								
T-note	0.00248				0.00264			
	(0.48)				(0.54)			
real T-note		-0.00595				-0.00428		
		(-1.43)				(-1.00)		
Aaa			-0.00419				-0.00239	
			(-0.76)				(-0.44)	
real Aaa				-0.0123***				-0.00958**
				(-3.08)				(-2.28)
N	570	570	570	570	570	570	570	570

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence, and common $AR(1)$ correlation; z statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e and $\hat{e}$ are the real value of the dollar and its permanent component, respectively.

Table 4.17. Industry Level Investment: FGLS, Pooled U.S. Manufacturing Industries, 1976-2005. Sample Splits by Markup and Import Competition. Adjustment for Common $AR(1)$ Correlation.

	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00774*	0.0188	-0.0000138	0.0235*	0.00123
	(1.92)	(1.56)	(-0.00)	(1.84)	(0.16)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	0.172	-0.956	-0.0581	-0.484	0.880*
	(0.77)	(-1.29)	(-0.14)	(-0.64)	(1.78)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-4.763***	-7.245*	-0.0259	-6.367***	-4.439
	(-2.70)	(-1.82)	(-0.01)	(-2.66)	(-0.82)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-1.747	11.65	-5.162	2.450	-12.04
	(-0.47)	(1.07)	(-1.00)	(0.35)	(-1.64)
Δy^i_{t-1}	0.391***	0.150**	0.509***	0.199**	0.303***
	(11.22)	(2.00)	(4.86)	(2.43)	(3.08)
Δoil_{t-1}	-0.0429**	0.0132	-0.0514	-0.0230	-0.0314
	(-2.56)	(0.27)	(-1.50)	(-0.41)	(-0.98)
Δr_{t-1}	-0.00958**	-0.00101	-0.0107	0.00724	-0.0133*
	(-2.28)	(-0.09)	(-1.27)	(0.53)	(-1.70)
N	570	270	300	270	300

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence, and common $AR(1)$ correlation; z statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e is the real value of the dollar.

Table 4.18. Prais-Winsten Estimation with PCSE: Sample Splits by Markup and Import Competition. Adjustment for Panel-specific $AR(1)$ Correlation.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00788	0.0178	0.00317	0.00879	0.00672
	(0.60)	(1.17)	(0.24)	(0.58)	(0.55)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.155	-0.179	-0.282	-0.358	0.167
	(-0.19)	(-0.16)	(-0.34)	(-0.32)	(0.19)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-7.989*	-12.59**	-9.866	-9.857**	-3.267
	(-1.94)	(-2.13)	(-1.28)	(-2.11)	(-0.38)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	2.509	9.997	4.401	6.095	-4.380
	(0.26)	(0.63)	(0.40)	(0.57)	(-0.38)
Δy^i_{t-1}	0.498***	0.387***	0.647***	0.455***	0.568***
	(4.02)	(3.04)	(3.67)	(3.31)	(3.66)
Δoil_{t-1}	-0.0579	-0.0393	-0.0727	-0.0642	-0.0537
	(-1.06)	(-0.64)	(-1.28)	(-0.95)	(-1.10)
Δr_{t-1}	-0.00598	-0.000889	-0.00993	-0.00143	-0.0105
	(-0.45)	(-0.06)	(-0.72)	(-0.09)	(-0.89)
N	570	270	300	270	300
R^2	0.121	0.122	0.138	0.126	0.116
RMSE	0.136	0.126	0.144	0.150	0.124
SSR	10.453	4.194	6.116	5.907	4.519

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence, and panel-specific $AR(1)$ correlation; z statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e is the real value of the dollar.

Table 4.19. Prais-Winsten Estimation with PCSE: Sample Splits by Markup and Import Competition. Adjustment for Common $AR(1)$ Correlation.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00769	0.0166	0.00280	0.0107	0.00434
	(0.56)	(1.00)	(0.21)	(0.65)	(0.35)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.176	-0.154	-0.246	-0.220	0.0669
	(-0.20)	(-0.14)	(-0.29)	(-0.18)	(0.07)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-6.569	-10.19*	-7.329	-8.675*	-2.316
	(-1.63)	(-1.69)	(-0.87)	(-1.92)	(-0.28)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	1.420	6.654	2.758	4.245	-4.462
	(0.14)	(0.40)	(0.25)	(0.39)	(-0.37)
Δy^i_{t-1}	0.409***	0.305**	0.604***	0.365***	0.523***
	(3.32)	(2.43)	(3.19)	(2.72)	(3.18)
Δoil_{t-1}	-0.0658	-0.0507	-0.0707	-0.0791	-0.0545
	(-1.14)	(-0.78)	(-1.21)	(-1.09)	(-1.07)
Δr_{t-1}	-0.00574	-0.00359	-0.00999	0.000626	-0.0119
	(-0.41)	(-0.23)	(-0.70)	(0.04)	(-0.96)
N	570	270	300	270	300
R^2	0.096	0.093	0.113	0.095	0.109
RMSE	0.140	0.131	0.147	0.155	0.125
SSR	11.024	4.544	6.352	6.335	4.610

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence, and common $AR(1)$ correlation; z statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e is the real value of the dollar.

Table 4.20. OLS with DKSE: Sample Splits by Markup and Import Competition. Robust to Third Order Autocorrelation.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00749	0.0156	0.00320	0.0111	0.00388
	(0.55)	(1.00)	(0.25)	(0.60)	(0.35)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.183	-0.206	-0.236	-0.194	0.0870
	(-0.36)	(-0.29)	(-0.36)	(-0.28)	(0.15)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-6.633**	-10.51***	-6.835	-8.641**	-2.973
	(-2.11)	(-4.21)	(-0.74)	(-2.49)	(-0.34)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	1.558	7.507	2.106	4.029	-4.024
	(0.26)	(0.86)	(0.19)	(0.68)	(-0.46)
Δy^i_{t-1}	0.414***	0.318**	0.562**	0.357***	0.549*
	(3.43)	(2.69)	(2.90)	(3.58)	(2.10)
Δoil_{t-1}	-0.0650	-0.0500	-0.0761	-0.0805	-0.0522
	(-1.50)	(-1.27)	(-1.43)	(-1.28)	(-1.64)
Δr_{t-1}	-0.00520	-0.0000619	-0.0108	-0.000582	-0.0111
	(-0.50)	(-0.00)	(-1.31)	(-0.05)	(-1.05)
N	570	270	300	270	300
R^2	0.097	0.096	0.105	0.093	0.113
RMSE	0.140	0.132	0.147	0.155	0.126

Notes: Statistics robust to heteroskedasticity, cross-sectional dependence and up to $AR(3)$; t statistics in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; e is the real value of the dollar.

Table 4.21. OLS with DKSE: Sample Splits by Markup and Import Competition. No Adjustment for Autocorrelation.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00749	0.0156	0.00320	0.0111	0.00388
	(0.56)	(1.00)	(0.24)	(0.65)	(0.33)
$(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-0.183	-0.206	-0.236	-0.194	0.0870
	(-0.22)	(-0.19)	(-0.29)	(-0.20)	(0.09)
$\chi^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	-6.633*	-10.51**	-6.835	-8.641*	-2.973
	(-1.93)	(-3.15)	(-0.62)	(-2.25)	(-0.33)
$\alpha^i_{t-1}(\tilde{\kappa}^i_{t-1})^{-1}\Delta e_{t-1}$	1.558	7.507	2.106	4.029	-4.024
	(0.19)	(0.62)	(0.16)	(0.55)	(-0.35)
Δy^i_{t-1}	0.414***	0.318**	0.562**	0.357***	0.549*
	(3.52)	(2.68)	(2.68)	(3.53)	(2.06)
Δoil_{t-1}	-0.0650	-0.0500	-0.0761	-0.0805	-0.0522
	(-1.21)	(-0.89)	(-1.30)	(-1.14)	(-1.13)
Δr_{t-1}	-0.00520	-0.0000619	-0.0108	-0.000582	-0.0111
	(-0.44)	(-0.00)	(-0.90)	(-0.04)	(-0.93)
N	570	270	300	270	300
R^2	0.097	0.096	0.105	0.093	0.113
RMSE	0.140	0.132	0.147	0.155	0.126

Notes: Statistics robust to heteroskedasticity and cross-sectional dependence; t statistics in parentheses; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$; e is the real value of the dollar.

Table 4.22. FGLS: Industry-specific, Total Trade Weighted Exchange Rates.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00868*	0.0193*	0.00325	0.0237*	0.00233
	(1.87)	(1.69)	(0.39)	(1.83)	(0.30)
Δter^i_{t-1}	-0.366***	-0.423**	-0.380**	-0.638***	-0.215
	(-3.78)	(-2.08)	(-2.31)	(-2.86)	(-1.32)
Δy^i_{t-1}	0.362***	0.157**	0.500***	0.183**	0.352***
	(9.66)	(2.17)	(4.83)	(2.27)	(3.54)
Δoil_{t-1}	-0.0332*	0.0129	-0.0498	-0.0153	-0.0158
	(-1.71)	(0.27)	(-1.44)	(-0.28)	(-0.49)
Δr_{t-1}	-0.00420	-0.000492	-0.0109	0.00732	-0.0120
	(-0.92)	(-0.04)	(-1.37)	(0.57)	(-1.57)
N	570	270	300	270	300

Notes: Statistics robust to heteroskedasticity and cross-sectional dependence; z statistics in parentheses; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 4.23. OLS with PCSE: Industry-specific, Total Trade Weighted Exchange Rates.

Investment	(1) All	(2) High markup	(3) Low markup	(4) High import competition	(5) Low import competition
Constant	0.00927	0.0163	0.00503	0.0134	0.00529
	(0.67)	(1.03)	(0.36)	(0.78)	(0.45)
Δter^i_{t-1}	-0.508	-0.523	-0.481	-0.659*	-0.338
	(-1.62)	(-1.50)	(-1.44)	(-1.78)	(-1.18)
Δy^i_{t-1}	0.405***	0.308*	0.551**	0.332*	0.559***
	(3.29)	(2.46)	(2.87)	(2.43)	(3.46)
Δoil_{t-1}	-0.0576	-0.0371	-0.0714	-0.0628	-0.0487
	(-0.99)	(-0.56)	(-1.23)	(-0.87)	(-0.98)
Δr_{t-1}	-0.00423	0.00153	-0.0101	0.00164	-0.0103
	(-0.31)	(0.09)	(-0.73)	(0.10)	(-0.87)
N	570	270	300	270	300
R^2	0.089	0.077	0.101	0.080	0.111
RMSE	0.140	0.133	0.147	0.156	0.125

Notes: Statistics robust to heteroskedasticity and cross-sectional dependence; z statistics in parentheses; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

CHAPTER 5

FIRM LEVEL ESTIMATES

This chapter begins with a discussion of my attempts to apply the methods of Chirinko et al. (1999) using the firm level data described in Chapter 3. In these efforts, I discover that the traditional method of constructing the user cost series with time-varying weights may be biased when including the time period of dramatic price decreases in information technology and computer related capital assets. I also find that investment is less sensitive to cash flow as an indicator of financial constraints when using more recent data. I then extend the work of Chirinko et al. (1999) to include real exchange rates in a firm level analysis of investment. Although I find no evidence of significant exchange rate effects on investment when pooling all U.S. manufacturing firms, I do find evidence of significant exchange rate effects on investment for firms that operate in industries with a high degree of exchange rate exposure using three alternative measures.

5.1 Replication

The study chosen for replication is Chirinko et al. (1999), which is referred to as the "benchmark" study in this chapter. As noted in Chapter 3, I do not have access to the actual data used in Chirinko et al. (1999), nor am I able to construct an exactly comparable dataset for the same time period (1981-1991) as in the original study. As a result, the analyses in this section are more of a test of whether I can reproduce the qualitative findings of Chirinko et al. (1999) with my data (1995-2010) and using their methods. I undertake this exercise in an attempt to set a reliable baseline for my own extension of their model.

Chirinko et al. (1999) estimate the following specification for the investment function:

$$\frac{I_{f,t}}{\hat{K}_{f,t-1}} = \delta_f + \sum_{h=0}^{6} \alpha_h \left(\frac{\Delta U_{i,t-h}}{U_{i,t-h-1}} \right) + \sum_{h=0}^{4} \beta_h \left(\frac{\Delta S_{f,t-h}}{S_{f,t-h-1}} \right) + \sum_{h=0}^{4} \gamma_h \left(\frac{CF_{f,t-h}}{\hat{K}_{f,t-h-1}} \right) + \epsilon_{i,t} \tag{5.1}$$

where f is a firm index, i is an industry index, t is the time period and δ_f is a firm-specific effect. $I_{f,t}$ is real firm investment, $\hat{K}_{f,t}$ is the real value of the firm's estimated capital stock measured at replacement cost, $S_{f,t}$ is the firm's real value of sales, and $CF_{f,t}$ is the firm's cash flow. Using my data, the user cost of capital, $U_{i,t}$, is industry-specific, and it is matched to the firm by the two-digit SIC code. For the initial attempt at replication, I use the user cost constructed with time-varying weights to match the methodology of Chirinko et al. (1999), who determined that annual lags of 0 to 6 for the user cost and lags of 0 to 4 for sales growth and the cash flow to capital ratio were appropriate for the initial OLS estimates.

Table 5.1. OLS Regressions: Comparison to Chirinko et al. (1999)

	Mean difference		First difference	
	Benchmark	Actual	Benchmark	Actual
$\Delta U_{i,t}/U_{i,t-1}$				
α_0	-0.088***	0.048	-0.055***	-0.061
	(0.016)	(0.038)	(0.018)	(0.046)
α_1	-0.155***	-0.056	-0.117***	-0.134**
	(0.014)	(0.043)	(0.022)	(0.059)
α_2	-0.123***	0.014	-0.086***	-0.054
	(0.014)	(0.048)	(0.023)	(0.064)
α_3	-0.024*	-0.173***	-0.001	-0.242***
	(0.014)	(0.050)	(0.025)	(0.068)
α_4	-0.037***	0.044	-0.038	0.0004
	(0.014)	(0.050)	(0.025)	(0.070)
α_5	-0.087***	-0.049	-0.101***	-0.131*
	(0.014)	(0.051)	(0.026)	(0.075)
α_6	0.012	0.005	-0.023	0.068
	(0.022)	(0.051)	(0.025)	(0.063)
SUM (α)	**-0.502*** **	**-0.167**	**-0.421*** **	**-0.552***
	(0.053)	**(0.131)**	**(0.114)**	**(0.310)**
$\Delta S_{f,t}/S_{f,t-1}$				
β_0	0.079***	0.156***	0.047***	0.113***
	(0.004)	(0.006)	(0.006)	(0.007)
β_1	0.033***	0.087***	0.004	0.041***
	(0.004)	(0.006)	(0.007)	(0.008)
β_2	0.029***	0.039***	0.006	0.003
	(0.005)	(0.006)	(0.007)	(0.009)
β_3	0.006	0.023***	0.011	-0.004
	(0.005)	(0.006)	(0.007)	(0.008)
β_4	0.006	0.013**	0.002	-0.009
	(0.005)	(0.005)	(0.006)	(0.006)
SUM (β)	**0.153*** **	**0.319*** **	**0.049*** [a]	**0.146*** **
	(0.012)	**(0.015)**	**(0.025)**	**(0.029)**
$CF_{f,t}/\hat{K}_{f,t-1}$				
γ_0	0.102***	-0.012***	0.130***	-0.009***

Continued on Next Page...

Table 5.1 – Continued

	Mean difference		First difference	
	Benchmark	Actual	Benchmark	Actual
	(0.004)	(0.001)	(0.005)	(0.002)
γ_1	0.101***	0.018***	0.105***	0.016***
	(0.004)	(0.002)	(0.005)	(0.002)
γ_2	0.036***	0.006***	0.041***	0.005**
	(0.004)	(0.002)	(0.005)	(0.002)
γ_3	0.018***	0.003	0.015***	0.001
	(0.004)	(0.002)	(0.005)	(0.002)
γ_4	0.009**	-0.002	0.003	-0.002
	(0.004)	(0.002)	(0.005)	(0.002)
SUM (γ)	**0.265*** **	**0.013*** **	**0.296*** **	**0.010**
	(0.007)	**(0.003)**	**(0.016)**	**(0.007)**
Observations	26,071	21,003	N/A	18,528
per group: min	N/A	2	N/A	1
per group: avg	N/A	8.6	N/A	7.6
per group: max	N/A	16	N/A	15
Number of firms	4,095	2,435	N/A	2,435
Time horizon	1981-1991	1995-2010	1982-1991	1996-2010

Notes: For comparability with the benchmark (Chirinko et al., 1999), standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample period for the benchmark estimates is 1981-1991, and the sample period for the actual estimates is 1995-2010.

[a] The benchmark reports this sum as 0.049, but the actual sum of the reported coefficients is 0.070.

Chirinko et al. (1999) begin their analysis with OLS regressions, which use mean or first differencing to sweep away the firm fixed effects. In Table 5.1, I present my initial attempt at replicating their methodology in those regressions. Starting with the mean difference results, Chirinko et al. (1999) find mostly negative and statistically significant coefficients for the user cost, with a statistically significant sum of -0.502. With my data, however, I find only three lags of the user cost to be negative, only one of which is statistically significant (lag three). In addition, the sum of the user cost coefficients (-0.167), while negative, is much smaller in absolute value and statistically insignificant.

For the sales accelerator, Chirinko et al. (1999) find a general trend of declining, positive coefficients, of which lags 0 through 2 are significant and with a statistically significant sum of 0.153. My data yield a similar declining trend of positive coefficients; however, mine tend to be greater in magnitude than those of Chirinko et al. (1999), and all of the lags are significant. The result is a greater magnitude for the long-run accelerator effect with a significant, coefficent sum of 0.319. This long-run value for the accelerator is similar to my short-run estimation of the accelerator effect based on a single lag in the industry level analysis of Chapter 4. The range of the estimates for all manufacturing industries in those analyses ranged from 0.375 to 0.424.

For the cash flow variable, Chirinko et al. (1999) report a trend of declining, positive and significant coefficients, with a significant sum of 0.265. My results yield a much different picture. First, the contemporaneous value of the cash flow to capital ratio is negative and significant, albeit small in absolute value. Lags one and two are positive and significant, but also much smaller in magnitude than that of the benchmark. Lag three is positive and lag four is negative, but both are very small and insignificant. The lags combine to yield a long-run coefficient sum of 0.013, which is positive and significant, but an order of magnitude smaller than that of Chirinko et al. (1999).

Using first differences, Chirinko et al. (1999) report negative coefficients for all lags of the user cost, but only four are statistically significant. The order of magnitude for these coefficients are similar to those of the benchmark mean difference results, and the long-run sum is estimated at a significant -0.421. Using my data, the three user cost lags that had negative coefficients in the mean difference estimation remain negative, yet all three are now statistically significant (although the fifth lag is only significant at 10%). The magnitudes of these three coefficients also become greater when using first differences. Two of the user cost lags (zero and two) switch signs from positive to negative in the first difference regression, but both values remain statistically insignificant. The larger negative values for the three significant coefficients, combined with the two flip-floppers, yield a marginally significant sum of -0.552. This value for the long-run user cost elasticity is more similar to the benchmark results for both regressions, but the level of significance is only 10%.

For sales growth, Chirinko et al. (1999) find only a single significant, positive coefficient, which is found on the contemporaneous value. The coefficients for the remaining lags, though positive, are all very small and insignificant. The resultant sum for the accelerator effect falls to a reported 0.049 (or 0.070 if we add the reported lags), which is only significant at 10%. My results again display a declining trend as the number of lags increases. In the first differences regression, however, the accelerator effect diminishes to an insignificant level after the first lag. My estimated coefficients for lags 3 and 4 even have a negative sign (although they are statistically insignificant). The long-run coefficient sum for the accelerator (0.146) using first differences is less than half of my mean difference estimate, which is qualitatively similar to the outcome in Chirinko et al. (1999).

Chirinko et al. (1999) find very similar estimates for the cash flow coefficients in the two regression techniques. By using first differences, the coefficients are all positive and, generally, very close to the mean difference estimates, which yields a similar sum of 0.296. The main difference is that the fourth lag becomes statistically insignificant. My first difference results for cash flow are also quite similar to my mean difference estimates. Lags zero through two retain the same signs and are significant at least at the 5% level. Even though the estimates are very similar, the long-run sum of 0.010 is now statistically insignificant.

There are several likely reasons behind the differences between my results and those of Chirinko et al. (1999), most of which derive from the fact that my dataset is quite different from theirs. First, Chirinko et al. (1999) include all types of U.S. firms from 1981-1991, whereas I include only U.S. manufacturing firms from 1995-2010. These two differences could be the reason why I generally find a stronger sales growth effect and a weaker cash flow effect than Chirinko et al. (1999). Also, my user cost data is more similar to that used in Spatareanu (2008), which could explain why I get fewer significant and even several positive coefficients for the user cost. Spatareanu (2008) covers only U.S. manufacturing firms from 1983-2001, and many of her estimates for the long-run sum of the user cost coefficients were small, insignificant, and sometimes positive.

As noted in Chapter 3, my sample (and to some extent that of Spatareanu (2008)) includes the time period for which computer-based capital goods experienced remarkable changes in price. With the sample in Chirinko et al. (1999) ending in 1991, it is likely that their measure of user cost would not have included much, if any, bias associated with these dramatic price changes. The use of time-varying weights in the construction of the user cost could be the reason why my results and those of Spatareanu (2008) yield more insignificant and positive coefficient estimates for the user cost. As a result, I test the sensitivity of my results to the choice of user cost measure. I re-run both the mean difference and the first difference regressions using alternate measures of the user cost: the two fixed-weighted user cost series ($UF_{i,t}^{99}$ and $UF_{i,t}^{05}$) and the chain-type user cost index series ($UC_{i,t}$).

Table 5.2. OLS Mean Difference Regressions: Alternative User Cost Measures

	Benchmark	$U_{i,t}$	$UF_{i,t}^{99}$	$UF_{i,t}^{05}$	$UC_{i,t}$
$\Delta U_{i,t}/U_{i,t-1}$					
α_0	-0.088***	0.048	-0.107***	-0.102***	-0.091**
	(0.016)	(0.038)	(0.038)	(0.037)	(0.041)
α_1	-0.155***	-0.056	-0.204***	-0.189***	-0.163***
	(0.014)	(0.043)	(0.043)	(0.042)	(0.046)
α_2	-0.123***	0.014	-0.110**	-0.116***	-0.115**
	(0.014)	(0.048)	(0.052)	(0.050)	(0.053)
α_3	-0.024*	-0.173***	-0.361***	-0.343***	-0.309***

Continued on Next Page...

Table 5.2 – Continued

	Benchmark	$U_{i,t}$	$UF_{i,t}^{99}$	$UF_{i,t}^{05}$	$UC_{i,t}$
	(0.014)	(0.050)	(0.053)	(0.051)	(0.055)
α_4	-0.037***	0.044	-0.095*	-0.076	-0.068
	(0.014)	(0.050)	(0.053)	(0.050)	(0.054)
α_5	-0.087***	-0.049	-0.245***	-0.192***	-0.185***
	(0.014)	(0.051)	(0.054)	(0.048)	(0.055)
α_6	0.012	0.005	-0.091*	-0.035	-0.060
	(0.022)	(0.051)	(0.050)	(0.045)	(0.055)
SUM (α)	**-0.502*** **	**-0.167**	**-1.213*** **	**-1.053*** **	**-0.992*** **
	(0.053)	**(0.131)**	**(0.116)**	**(0.086)**	**(0.152)**
$\Delta S_{f,t}/S_{f,t-1}$					
β_0	0.079***	0.156***	0.150***	0.147***	0.154***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
β_1	0.033***	0.087***	0.082***	0.079***	0.086***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
β_2	0.029***	0.039***	0.037***	0.034***	0.039***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
β_3	0.006	0.023***	0.022***	0.019***	0.024***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
β_4	0.006	0.013**	0.013**	0.010**	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
SUM (β)	**0.153*** **	**0.319*** **	**0.303*** **	**0.290*** **	**0.316*** **
	(0.012)	**(0.015)**	**(0.015)**	**(0.015)**	**(0.015)**
$CF_{f,t}/\hat{K}_{f,t-1}$					
γ_0	0.102***	-0.012***	-0.012***	-0.012***	-0.012***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
γ_1	0.101***	0.018***	0.017***	0.018***	0.017***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
γ_2	0.036***	0.006***	0.006***	0.006***	0.006***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
γ_3	0.018***	0.003	0.003*	0.004**	0.003*
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
γ_4	0.009**	-0.002	-0.002	-0.001	-0.002
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
SUM (γ)	**0.265*** **	**0.013*** **	**0.014*** **	**0.015*** **	**0.013*** **
	(0.007)	**(0.003)**	**(0.003)**	**(0.003)**	**(0.003)**
Observations	26,071	21,003	21,003	21,003	21,003
per group: min	N/A	2	2	2	2
per group: avg	N/A	8.6	8.6	8.6	8.6
per group: max	N/A	16	16	16	16
Number of firms	4,095	2,435	2,435	2,435	2,435
Time horizon	1981-1991	1995-2010	1995-2010	1995-2010	1995-2010

Notes: For comparability with the benchmark (Chirinko et al., 1999), standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5.2, I present the results for the mean difference estimations using the alternative measures of the user cost. The first two columns are the same as the first two columns in Table 5.1, with the benchmark results of Chirinko et al. (1999) and my results using the time-varying weighted user cost series ($U_{i,t}$). The third and fourth columns report the results using the 1999 and 2005 fixed-weighted user costs, respectively. These results suggest that using a fixed weighting scheme makes a dramatic difference in the signs, magnitudes and significance levels of the user cost coefficients for my sample. First, for both the 1999 and 2005 UF results, all of the estimated user cost coefficients are now negative. Second, using the 1999 UF yields statistical significance of at least 10% for all seven coefficients, while using the 2005 UF yields five significant coefficients (all at 1%). Lastly, the long-run sum of coefficients, which Chirinko et al. (1999) use to estimate the true user cost elasticity, is negative, highly significant, and over twice the magnitude of the benchmark sum. The results for the chain-type user cost coefficients, reported in the last column, are similar to those of the 2005 UF, with the same five coefficients significant at least at the 5% level. The three user cost elasticity estimates using the UF and UC weighting schemes range from -1.213 to -0.992, as indicated by the sum of coefficients. These estimates are much closer to the magical value of -1 implied by investment models that assume Cobb-Douglas production functions.

The results for both the sales growth and cash flow coefficients are largely unaffected by the choice of user cost measure, which suggests that any bias associated with the different weighting schemes affects only the user cost estimates. The range of estimates for the accelerator effect across the different regressions with my data is 0.290 to 0.319, which suggests that firm sales have a stronger effect on investment for manufacturing firms and/or since 1991. On the other hand, the much smaller magnitudes for the individual cash flow coefficients and their long-run sums, suggests that liquidity constraints have a much smaller effect for manufacturing firms and/or since 1991.

Table 5.3. OLS First Difference Regressions: Alternative User Cost Measures

	Benchmark	$U_{i,t}$	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
$\Delta U_{i,t}/U_{i,t-1}$					
α_0	-0.055***	-0.061	-0.086*	-0.085*	-0.092*
	(0.018)	(0.046)	(0.048)	(0.048)	(0.050)
α_1	-0.117***	-0.134**	-0.176***	-0.189***	-0.161**
	(0.022)	(0.059)	(0.065)	(0.064)	(0.066)
α_2	-0.086***	-0.054	-0.081	-0.078	-0.110
	(0.023)	(0.064)	(0.074)	(0.074)	(0.076)
α_3	-0.001	-0.242***	-0.302***	-0.287***	-0.285***
	(0.025)	(0.068)	(0.077)	(0.074)	(0.082)
α_4	-0.038	0.0004	-0.002	0.009	-0.016
	(0.025)	(0.070)	(0.079)	(0.076)	(0.082)
α_5	-0.101***	-0.131*	-0.147*	-0.126*	-0.144*
	(0.026)	(0.075)	(0.077)	(0.068)	(0.055)

Continued on Next Page...

Table 5.3 – Continued

	Benchmark	$U_{i,t}$	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
α_6	-0.023	0.068	0.093	0.095	0.079
	(0.025)	(0.063)	(0.067)	(0.061)	(0.069)
SUM (α)	**-0.421*****	**-0.552***	**-0.702****	**-0.662****	**-0.729****
	(0.114)	**(0.310)**	**(0.347)**	**(0.330)**	**(0.372)**
$\Delta S_{f,t}/S_{f,t-1}$					
β_0	0.047***	0.113***	0.113***	0.113***	0.113***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
β_1	0.004	0.041***	0.041***	0.041***	0.041***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)
β_2	0.006	0.003	0.004	0.004	0.003
	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
β_3	0.011	-0.004	-0.004	-0.004	-0.004
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
β_4	0.002	-0.009	-0.009	-0.009	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
SUM (β)	**0.049***	**0.146*****	**0.145*****	**0.146*****	**0.145*****
	(0.025)	**(0.029)**	**(0.029)**	**(0.029)**	**(0.029)**
$CF_{f,t}/\hat{K}_{f,t-1}$					
γ_0	0.130***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
γ_1	0.105***	0.016***	0.016***	0.016***	0.016***
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
γ_2	0.041***	0.005**	0.005**	0.005**	0.005**
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
γ_3	0.015***	0.001	0.001	0.001	0.001
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
γ_4	0.003	-0.002	-0.002	-0.002	-0.002
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
SUM (γ)	**0.296*****	**0.010**	**0.011**	**0.012***	**0.010**
	(0.016)	**(0.007)**	**(0.007)**	**(0.007)**	**(0.007)**
Observations	N/A	18,528	18,528	18,528	18,528
per group: min	N/A	2	2	2	2
per group: avg	N/A	7.6	7.6	7.6	7.6
per group: max	N/A	15	15	15	15
Number of firms	N/A	2,435	2,435	2,435	2,435
Time horizon	1982-1991	1996-2010	1996-2010	1996-2010	1996-2010

Notes: For comparability with the benchmark (Chirinko et al., 1999), standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.3 presents the results for the first difference estimations using the alternate measures of the user cost. Under this method, the different weighting schemes have a much less dramatic effect on the user cost coefficient estimates. The three negative and significant coefficients from the time-varying user cost regression retain their signs and a similar level of significance for both fixed-weighted and the chain-type regressions. These three coefficients, however, tend to be a bit larger in absolute value for all three alternative user cost measures. The biggest difference is that the coefficient on the contemporaneous value of the user cost becomes significant at the 10% level for both UF and the UC regressions. As a result, the estimates for the user cost elasticity range from -0.729 to -0.662, and all three are significant at the 5% level. Interestingly, the coefficient estimates and standard errors for both the sales accelerator and cash flow variables remain virtually unchanged across the four first difference regressions. This finding adds support to my earlier conclusion that any bias associated with different weighting schemes for the user cost affects only the estimated user cost coefficients.

Overall, by comparing the OLS results obtained from my data with those of Chirinko et al. (1999), I find that the coefficient estimates for sales growth and cash flow are not sensitive to the measure of the user cost, but do seem to have changed in regards to the magnitude of their overall effect on investment since the time period of the benchmark study. The accelerator effect seems to carry more weight and liquidity constraints less for U.S. manufacturing firms during 1995-2010. More importantly, the coefficient estimates for the user cost are very sensitive to the choice of weighting scheme used in its construction. It is quite possible that the low estimates of the user cost elasticity obtained in the benchmark study (and even more so in Spatareanu, 2008) are due to the bias associated with the measurement of the user cost with time-varying weights.

Chirinko et al. (1999) suggest that their estimates may be biased downward from unity due to simultaneity between investment shocks and interest rates. They also suggest that firm investment shocks may be contemporaneously correlated with sales and cash flow or that industry investment shocks may affect the relative prices of capital goods. As a result, they perform instrumental variables estimation. They use three different transformations to remove the fixed effects: mean differences, first differences and orthogonal deviations. For the mean difference and orthogonal deviations the instruments include the untransformed lags one through nine for the user cost and the untransformed lags one through seven for sales and cash flow. Chirinko et al. (1999) note that the mean difference estimates are problematic, because the mean difference transformation ensures that lags of the predetermined regressors, which are used as instruments, are correlated with the error term. As a result, I do not attempt to replicate the mean difference regressions. The first difference IV estimates performed in the benchmark study, however, suffer a different problem. Starting with the first difference transformation of the second lag of all three explanatory variables, the instruments are perfectly collinear with those variables. Chirinko et al. (1999) recognize that lags beyond the first year are perfectly predicted by the instruments, but they fail to acknowledge the econometric problems associated with this situation. In fact, these lagged regressors are simply transformations of the instruments, which ensures that the instruments are also correlated with the error term.[1] The orthogonal deviations transformation does not suffer from the aforementioned problems, so for replication purposes I reproduce that method, only.

Table 5.4. IV Regression (Orthogonal Deviations): Alternative User Cost Measures

	Benchmark	$U_{i,t}$	$UF_{i,t}^{99}$	$UF_{i,t}^{05}$	$UC_{i,t}$
$\Delta U_{i,t}/U_{i,t-1}$					
α_0	-0.020	0.125***	-0.052	-0.079*	0.026
	(0.080)	(0.046)	(0.052)	(0.045)	(0.055)
α_1	-0.212***	-0.011	-0.147***	-0.174***	-0.084
	(0.037)	(0.048)	(0.054)	(0.050)	(0.056)
α_2	-0.128***	0.041	-0.120*	-0.153***	-0.069
	(0.033)	(0.055)	(0.062)	(0.057)	(0.067)
α_3	-0.023	-0.078	-0.242***	-0.265***	-0.144**
	(0.029)	(0.049)	(0.059)	(0.054)	(0.057)
α_4	-0.051*	0.069	-0.037	-0.025	0.015
	(0.030)	(0.050)	(0.057)	(0.051)	(0.060)
α_5	-0.095**	-0.051	-0.211***	-0.184***	-0.118*
	(0.042)	(0.055)	(0.055)	(0.048)	(0.063)
α_6	-0.028	0.125**	0.041	0.077	0.107*
	(0.049)	(0.055)	(0.054)	(0.045)	(0.062)
SUM (α)	**-0.557*****	**0.231**	**-0.769*****	**-0.801*****	**-0.266**
	(0.157)	**(0.202)**	**(0.228)**	**(0.152)**	**(0.275)**
$\Delta S_{f,t}/S_{f,t-1}$					
β_0	-0.106	0.179***	0.173***	0.163***	0.179***
	(0.130)	(0.008)	(0.008)	(0.008)	(0.008)
β_1	0.074***	0.103***	0.100***	0.092***	0.104***
	(0.018)	(0.007)	(0.007)	(0.007)	(0.007)
β_2	0.051***	0.054***	0.052***	0.046***	0.056***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
β_3	0.033***	0.036***	0.035***	0.030***	0.037***
	(0.010)	(0.007)	(0.007)	(0.007)	(0.006)
β_4	0.031***	0.017***	0.017***	0.014***	0.019***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
SUM (β)	**0.084**	**0.389*****	**0.376*****	**0.344*****	**0.395*****
	(0.107)	**(0.023)**	**(0.023)**	**(0.024)**	**(0.022)**
$CF_{f,t}/\hat{K}_{f,t-1}$					
γ_0	0.514***	0.016**	0.015**	0.010	0.015**
	(0.097)	(0.007)	(0.007)	(0.006)	(0.006)
γ_1	-0.053	0.027***	0.026***	0.024***	0.026***
	(0.039)	(0.004)	(0.004)	(0.004)	(0.004)
γ_2	0.010	0.013***	0.013***	0.011***	0.013***
	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)

Continued on Next Page...

[1] Modern IV estimation programs, such as *ivreg2* by Baum et al. (2010), have built-in tests for collinearity. When trying to replicate the first difference IV estimation, *ivreg2* will not process the estimation as outlined in the benchmark study.

Table 5.4 – Continued

	Benchmark	$U_{i,t}$	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
γ_3	-0.002	-0.0001	-0.0003	-0.001	-0.0003
	(0.008)	(0.002)	(0.002)	(0.002)	(0.002)
γ_4	0.002	0.006**	0.006**	0.004*	0.006**
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
SUM (γ)	**0.472*** **	**0.061*** **	**0.060*** **	**0.048*** **	**0.059*** **
	(0.052)	**(0.015)**	**(0.015)**	**(0.015)**	**(0.015)**
Observations	N/A	13,838	13,838	13,838	13,838
per group: min	N/A	0	0	0	0
per group: avg	N/A	6.99	6.99	6.99	6.99
per group: max	N/A	13	13	13	13
Number of firms	N/A	1,981	1,981	1,981	1,981
Time horizon	1982-1991	1996-2010	1996-2010	1996-2010	1996-2010
Number of instruments		23	23	23	23
$AR(1)$ test		$z = -62.10$	$z = -62.46$	$z = -63.10$	$z = -62.28$
H_o: $AR(1)$ not present		$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$AR(2)$ test		$z = -5.21$	$z = -5.23$	$z = -5.28$	$z = -5.20$
H_o: $AR(2)$ not present		$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$AR(3)$ test		$z = -1.60$	$z = -1.63$	$z = -1.61$	$z = -1.61$
H_o: $AR(3)$ not present		$p = 0.110$	$p = 0.104$	$p = 0.108$	$p = 0.107$
Sargan overid. test		$J = 35.21$	$J = 36.39$	$J = 28.03$	$J = 34.95$
H_o: instruments are valid		$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$

Notes: For comparability with the benchmark (Chirinko et al., 1999), standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5.4, I compare the results of IV estimation, using the orthogonal deviations transformation and all four measures of user cost, to the results of the benchmark study. As noted in Chirinko et al. (1999), the best comparison for IV estimation on orthogonal deviations is with that of the OLS mean difference results. By comparing the benchmark IV results in Table 5.4 with the benchmark OLS results in Table 5.1, one can see that the individual user cost coefficient estimates and their long-run sum (-0.502 for OLS and -0.577 for IV) are not that different in terms of sign, magnitude, and level of significance. The results for the sales accelerator coefficients, however, change in sign, magnitude and significance for the contemporaneous value, which leads to a much smaller and insignificant positive value of 0.084 for the long run sum. As noted in the industry level analysis in Chapter 4, a positive and significant accelerator effect is one of the most durable results within the investment function literature, so this change in results must certainly have raised red flags for Chirinko et al. (1999). The individual cash flow coefficients are also quite different using IV, with only a single positive and significant coefficient on the contemporaneous value. In addition, the magnitude of this coefficient is four to five times larger than the first or mean difference OLS result, which leads to the larger, long run sum of 0.472.

Comparing the results between IV and OLS for my data and using the time-varying weighted user cost, however, presents an entirely different picture. The IV estimates for the user cost coefficients now include two significant coefficients, and both of them are positive. As a result, the long-run sum is now positive, although still insignificant. On the other hand, the estimated coefficients for the sales accelerator and the cash flow variable do not change all that much in terms of sign, magnitude, or significance. This result for sales and cash flow actually holds across all of the alternate measures of the user cost. What is quite different from using my data is that the user cost IV estimates for the two fixed-weighted series are relatively unchanged from the OLS estimates. The long-run estimates of the user cost elasticity, though smaller in absolute value, still contain the theoretical value of negative one in their 95% confidence intervals, which adds relevance to my assertion that the user cost is potentialy mismeasured with time-varying weights. Surprisingly, the estimates using the chain-type weighted user cost yield quite different results than the fixed-weight estimates under IV estimation. The IV estimates yield only three significant coefficients, one of which (the sixth lag) being positive. As a result, the long run sum declines dramatically to -0.266 and is now insignificant.

In order to perform the orthogonal deviations IV estimations with my data, I used the *xtabond2* command in Stata, which was developed in Roodman (2009). Like *ivreg2*, which was used in the industry level analysis, this command provides today's researchers with more post-estimation diagnostics than were available for Chirinko et al. (1999). In the bottom section of Table 5.4, I present the results for tests of autocorrelation and identification, which are now standard for IV/GMM estimation. The test for autocorrelation is the Arellano-Bond test, which is designed to test whether some of the untransformed lagged values are invalid to use as instruments. The idea is that to check for first-order correlation in levels, one looks for second-order correlation in differences.[2] If there is evidence of second-order correlation in differences, then the first and second untransformed lags of the regressors are invalid instruments, because they are correlated with the error term. The test for overidentifying restrictions is the Hansen-Sargen test, which assesses the adequacy of the instruments in an overidentified context. A rejection of the Hansen-Sargen test questions the suitability of the instrument set, in particular the orthogonality of the instruments to

[2] As noted in Roodman (2009), there is no such trick for orthogonal deviations, so the test is run using a first difference transformation.

the error term. The results of the Arellano-Bond tests for autocorrelation in Table 5.4 suggest that lags three or greater are necessary for the untransformed instruments to be valid no matter which measure of the user cost is used. In addition, the tests of overidentifying restrictions are soundly rejected for all of the regressions using my data.

Interestingly, the orthogonal deviation IV results were the best option of the three transformations in Chirinko et al. (1999). Although biased (knowingly or not), the mean and first difference IV results for the user cost elasticity were -0.254 and -0.060, respectively; and both were insignificant. In addition, the pattern discussed above for the accelerator and cash flow was present in those regressions, as well. I make this observation, because the solution in Chirinko et al. (1999) was to reduce the number of lagged user cost regressors in an attempt to address problems with identification. By limiting the lags of the user cost to zero through two, however, they basically guaranteed a low estimate of the user cost elasticity without explicitly addressing the problems associated with identification. In contrast, I attempt to create a valid set of instruments before adjusting the econometric model.

One of the decisions in Chirinko et al. (1999) is to use IV estimation. I find this interesting, because they reference Arellano (1988) and Arellano and Bover (1995) in regards to the use of orthogonal deviations. Both of those articles, however, were written in the context of what many econometricians today would refer to as "difference-GMM" (see, for example Baum (2006), Bond (2002), and Roodman (2009)). Similar to the IV estimation in Chirinko et al. (1999), difference-GMM transforms the data by either first differences or orthogonal deviations to remove the fixed effects, and then uses a large set of lagged, untransformed variables as instruments. The difference, however, is that it uses what Roodman (2009) refers to as "GMM-style instruments," where each time period has its own set of valid lags. With difference-GMM the problems of collinearity identified in the IV first difference regressions are eliminated by construction. Roodman (2009) notes, however, that using the first difference transformation in difference-GMM results in an unnecessary loss of observations in unbalanced panels with gaps. He recommends using orthogonal deviations in this scenario; and since my panel is unbalanced with gaps, I follow this recommendation.

Table 5.5. Difference GMM (Orthogonal Deviations): Alternative User Cost Measures

	$U_{i,t}$	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
$\Delta U_{i,t}/U_{i,t-1}$				

Continued on Next Page...

Table 5.5 – Continued

	$U_{i,t}$	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
α_0	0.021	-0.124***	-0.110***	-0.105**
	(0.040)	(0.041)	(0.039)	(0.043)
α_1	-0.063	-0.209***	-0.195***	-0.162***
	(0.046)	(0.047)	(0.045)	(0.049)
α_2	-0.010	-0.129**	-0.121**	-0.129**
	(0.049)	(0.054)	(0.051)	(0.056)
α_3	-0.185***	-0.353***	-0.325***	-0.302***
	(0.051)	(0.055)	(0.052)	(0.057)
α_4	0.022	-0.094*	-0.067	-0.073
	(0.052)	(0.055)	(0.051)	(0.057)
α_5	-0.092*	-0.256***	-0.190***	-0.203***
	(0.053)	(0.056)	(0.050)	(0.058)
α_6	-0.004	-0.070	-0.016	-0.050
	(0.053)	(0.052)	(0.047)	(0.057)
SUM (α)	**-0.312****	**-1.233*****	**-1.024*****	**-1.024*****
	(0.146)	**(0.132)**	**(0.099)**	**(0.173)**
$\Delta S_{f,t}/S_{f,t-1}$				
β_0	0.200***	0.188***	0.183***	0.196***
	(0.007)	(0.007)	(0.008)	(0.007)
β_1	0.114***	0.105***	0.100***	0.111***
	(0.007)	(0.007)	(0.007)	(0.007)
β_2	0.056***	0.050***	0.046***	0.055***
	(0.007)	(0.007)	(0.007)	(0.006)
β_3	0.040***	0.036***	0.032***	0.039***
	(0.007)	(0.006)	(0.006)	(0.006)
β_4	0.026***	0.024***	0.021***	0.026***
	(0.006)	(0.006)	(0.006)	(0.006)
SUM (β)	**0.435*****	**0.403*****	**0.383*****	**0.427*****
	(0.020)	**(0.020)**	**(0.020)**	**(0.019)**
$CF_{f,t}/\hat{K}_{f,t-1}$				
γ_0	-0.005	-0.008**	-0.008***	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
γ_1	0.019***	0.018***	0.018***	0.019***
	(0.002)	(0.002)	(0.002)	(0.002)
γ_2	0.008***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
γ_3	0.002	0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
γ_4	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
SUM (γ)	**0.022*****	**0.016****	**0.016****	**0.018*****
	(0.007)	**(0.007)**	**(0.007)**	**(0.007)**
Observations	18,568	18,568	18,568	18,568
per group: min	0	0	0	0
per group: avg	7.63	7.63	7.63	7.63
per group: max	15	15	15	15
Number of firms	2,435	2,435	2,435	2,435
Time horizon	1996-2010	1995-2009	1995-2009	1995-2009

Continued on Next Page…

Table 5.5 – Continued

	$U_{i,t}$	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
Number of instruments	342	342	342	342
$AR(1)$ test	$z = -39.70$	$z = -39.76$	$z = -39.68$	$z = -39.74$
H_o: $AR(1)$ not present	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$AR(2)$ test	$z = -4.24$	$z = -4.26$	$z = -4.23$	$z = -4.24$
H_o: $AR(2)$ not present	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$AR(3)$ test	$z = -1.11$	$z = -1.12$	$z = -1.14$	$z = -1.12$
H_o: $AR(3)$ not present	$p = 0.268$	$p = 0.262$	$p = 0.255$	$p = 0.263$
Sargan overid. test	$J = 1040.00$	$J = 994.08$	$J = 967.35$	$J = 1044.02$
H_o: instruments are valid	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$

Notes: For comparability with the benchmark (Chirinko et al., 1999), standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

So, before changing the model specification, I run difference-GMM estimations using the orthogonal deviations transformation and GMM-style instruments in an attempt to find a suitable instrument set. In Table 5.5, I compare the results of GMM estimation for all four measures of the user cost. As a starting point I restrict the available lags of the untransformed variables to be used as instruments to the same lag structure used in the IV estimation. Specifically, the GMM-style instrument set includes lags of one and up to nine for the user cost and lags of one and up to seven for sales and cash flow. Using the GMM-style instruments with difference GMM on my data yield a very different outcome than IV estimation. For the time-varying weighted measure of the user cost, five of the seven coefficients are negative and two are significant at least at the 10% level. The long run sum of -0.312 is now significant at 5%, and the magnitude falls in between the mean and first difference OLS results. At the same time, the individual coefficient estimates for the sales and cash flow variables are practically the same as the corresponding mean difference OLS estimates in terms of sign, magnitude, and significance. The lone exception is that the coefficient for the contemporaneous value of the cash flow is no longer significant. The long run sums for sales and cash flow are slightly larger than in the OLS results, but they maintain the same relative orders of magnitude and all are significant at least at 5%. More importantly, all of the estimated coefficients (both individual and the long run sum) for the two fixed-weight and the chain-type user costs are practically the same as the corresponding mean difference OLS estimates in terms of sign, magnitude, and significance. The estimated sales cash flow coefficients are virtually unchanged, as well. The major difference is that the long-run sum of the cash flow effect drops to the 5% level of significance for the two fixed-weight user cost series.

Clearly, the GMM-style instruments of difference-GMM are superior to the IV-style instruments used in the IV regressions of the benchmark study. In fact, the results presented so far suggest that there is nothing to gain from IV/GMM estimation and that the OLS mean difference results are consistent. If this is true, then using IV/GMM estimation techniques should not be preferred to OLS, because it results in a loss of efficiency. When looking at the IV/GMM diagnostics reported in the bottom section of Table 5.5, however, one can see that the current instrument set is less than satisfactory. First, the number of instruments used in difference-GMM is 342, which is much larger than the 23 used in the IV regressions. Roodman (2009) notes that instrument proliferation can overfit endogenous variables, which increases the bias associated with their estimation in finite samples. The general rule of thumb is to have fewer instruments than the number of groups. The number of firms used in the difference-GMM estimation is 2,435, so that particular rule is satisfied, but Roodman (2009) also recommends testing the sensitivity of the results to a reduction in the instrument count. Second, the Hansen-Sargan test of overidentifying restrictions suggests that the current instrument set is not valid. Another effect of instrument proliferation is that this test is weakened in the presence of too many instruments, so the strong rejection of the null hypothesis for the Hansen-Sargen test suggests that the instrument count should be reduced. Last, the results of the $AR(2)$ test in first differences indicates the presence of autocorrelation in levels. The presence of autocorrelation itself can be corrected with robust standard errors, but it suggests that the instrument set should start with lags of three or greater. The first and second lags are currently in the instrument set, which could be one reason for the sound rejection of the test of overidentification.

Autocorrelation and heteroskedasticity are never mentioned by Chirinko et al. (1999), so it is quite possible that they failed to address these issues in their analysis. The post-estimation diagnostics discussed above indicate that standard errors should at least be adjusted to account for autocorrelation. The test for autocorrelation also can be biased in the presence of cross-sectional dependence, so Roodman (2009) suggests including time dummies in any difference-GMM estimation to alleviate such a bias. Lastly, with GMM estimation it is common practice not to assume homoskedasticity and automatically report robust standard errors. As a result, I rerun the difference-GMM regressions with a smaller instrument set, and I include time dummies and report standard errors that are robust to arbitrary heteroskedasticity and autocorrelation. After testing different lag structures, I choose a GMM-style instrument set that restricts the lagged levels of user cost growth from four to six, to only lag three for sales growth, and to only lag four for the cash flow to capital ratio. This instrument set is chosen to minimize the number of instruments, while meeting the requirements for the overidentifying restrictions.

Table 5.6. Robust Difference-GMM (Orthogonal Deviations): Alternative User Cost Measures

	$U_{i,t}$	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
$\Delta U_{i,t}/U_{i,t-1}$				
α_0	-0.093	-0.165**	-0.197**	-0.103
	(0.079)	(0.082)	(0.082)	(0.074)
α_1	-0.171*	-0.217**	-0.236**	-0.191**
	(0.090)	(0.087)	(0.097)	(0.086)
α_2	0.076	0.085	0.116	0.069
	(0.111)	(0.124)	(0.115)	(0.115)
α_3	-0.196**	-0.265***	-0.189**	-0.277***
	(0.098)	(0.103)	(0.090)	(0.099)
α_4	0.065	0.007	0.041	0.033
	(0.077)	(0.067)	(0.052)	(0.071)
α_5	-0.106	-0.116	-0.048	-0.145**
	(0.070)	(0.072)	(0.067)	(0.074)
α_6	-0.008	-0.024	-0.010	0.054
	(0.127)	(0.096)	(0.088)	(0.107)
SUM (α)	**-0.433***	**-0.695*****	**-0.521****	**-0.561****
	(0.252)	**(0.266)**	**(0.243)**	**(0.268)**
$\Delta S_{f,t}/S_{f,t-1}$				
β_0	0.253***	0.255***	0.242***	0.265***
	(0.063)	(0.068)	(0.073)	(0.065)
β_1	0.248***	0.250***	0.235***	0.250***
	(0.082)	(0.082)	(0.080)	(0.083)
β_2	0.017	0.015	0.015	0.017
	(0.019)	(0.019)	(0.018)	(0.019)
β_3	0.020	0.020	0.011	0.023
	(0.037)	(0.036)	(0.035)	(0.036)
β_4	-0.026	-0.038	-0.042	-0.033
	(0.051)	(0.050)	(0.049)	(0.050)
SUM (β)	**0.512*****	**0.502*****	**0.461*****	**0.522*****
	(0.137)	**(0.133)**	**(0.134)**	**(0.134)**
$CF_{f,t}/\hat{K}_{f,t-1}$				
γ_0	-0.039	-0.042	-0.042	-0.042
	(0.033)	(0.034)	(0.035)	(0.034)
γ_1	0.035	0.030	0.029	0.026
	(0.024)	(0.023)	(0.023)	(0.023)
γ_2	-0.006	-0.003	0.001	-0.004
	(0.020)	(0.020)	(0.021)	(0.020)
γ_3	0.011	0.011	0.010	0.012
	(0.009)	(0.009)	(0.009)	(0.009)
γ_4	0.015	0.017	0.020	0.016
	(0.013)	(0.014)	(0.013)	(0.013)
SUM (γ)	**0.016**	**0.013**	**0.018**	**0.009**
	(0.038)	**(0.041)**	**(0.041)**	**(0.040)**

Continued on Next Page...

Table 5.6 – Continued

	$U_{i,t}$	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
Observations	18,568	18,568	18,568	18,568
per group: min	0	0	0	0
per group: avg	7.63	7.63	7.63	7.63
per group: max	15	15	15	15
Number of firms	2,435	2,435	2,435	2,435
Time horizon	1995-2009	1995-2009	1995-2009	1995-2009
Number of instruments	90	90	90	90
$AR(1)$ test	$z = -3.59$	$z = -3.56$	$z = -3.56$	$z = -3.55$
H_o: $AR(1)$ not present	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$AR(2)$ test	$z = -2.21$	$z = -2.26$	$z = -2.30$	$z = -2.38$
H_o: $AR(2)$ not present	$p = 0.027$	$p = 0.024$	$p = 0.021$	$p = 0.018$
$AR(3)$ test	$z = -0.90$	$z = -1.18$	$z = -1.15$	$z = -1.22$
H_o: $AR(3)$ not present	$p = 0.370$	$p = 0.237$	$p = 0.251$	$p = 0.222$
Hansen overid. test (robust)	$J = 56.23$	$J = 56.40$	$J = 63.70$	$J = 53.33$
H_o: instruments are valid	$p = 0.541$	$p = 0.535$	$p = 0.283$	$p = 0.649$
Hausman specification test	$\chi^2 = 41.15$	$\chi^2 = 9.81$	$\chi^2 = 9.19$	$\chi^2 = 16.59$
H_o: No sys. diff from OLS	$p = 0.0009$	$p = 0.9115$	$p = 0.9342$	$p = 0.4825$

Notes: For comparability with the benchmark (Chirinko et al., 1999), standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results of the robust difference-GMM regressions with the limited instrument set are presented in Table 5.6 for all four measures of the user cost. For the time-varying user cost, there remain only two negative and significant coefficients. The rest of the coefficients are insignificant, with two being positive. The long run sum for the UCE (-0.433) does not change much in magnitude from the previous GMM regression (-0.312), but the significance level drops to 10%. Overall, there is not much difference in these estimates from the previous GMM regression.

Comparing the fixed-weight and chain-type user cost coefficients to the previous GMM regressions, one can see the bias associated with too many instruments and with non-robust estimation. Instead of five, each regression yields only three negative and significant user cost coefficients: the contemporaneous value and the first and third lags for the two-fixed weight series, and the first, third and fifth lags for the chained user cost index. The second and fourth lags for all three regressions change from being negative and significant to positive and insignificant. The long run sums now range from -0.521 to -0.695 and all are significant at least at the 5% level; as a result, the 95% confidence intervals for the user cost elasticity no longer bound the theoretical value of negative one.

The estimated sales growth coefficients are very similar in terms of signs, magnitudes and signficance across the four robust estimations. Although the long run sums are similar to the previous GMM estimates, the individual coefficients yield a different pattern. No longer are all of the lags significant with a declining trend in magnitude. Instead the contemporaneous values and the first lags are significant, positive, and all very close to 0.250. The second and third lags are still positive but insignificant, and the fourth lag is now negative and insignificant. The estimated cash flow coefficients are similar to the sales coefficients in that they are very similar in terms of signs and magnitude across the four robust estimations. The only negative coefficients show up in the contemporaneous value (with a range of -0.039 to -0.042) and the second lag (with a range of -0.006 to 0.001). All of the other individual coefficents are small, positive, and similar in magnitude to previous estimates. This result holds for the long run sums, as well. The primary difference for the robust cash flow estimates is the lack of any statistical significance for the individual coefficents or the long run sums.

Turning to the post-estimation diagnostics in Table 5.6, one can see that the Arellano-Bond $AR(1)$ and $AR(2)$ tests are still rejected at 5%. The instrument set, however, has been adjusted to deal with this with the lags starting at three or four. The test for overidentifying restrictions uses the Hansen J statistic, which is robust to arbitrary heteroskedasticity and autocorrelation. For all four regressions, I fail to reject the null hypothesis of correct model specification and valid overidentifying restrictions, which suggests that the instrument set is suitable. The final diagnostic test in Table 5.6 is a Hausman specification test, which compares these results to an equivalent OLS regression. The null hypothesis is that there is no systematic difference in the estimated coefficients between the two regressions. A failure to reject the null implies that estimation by OLS is consistent and difference-GMM is unnecessary. For the time-varying weighted user cost, I reject the null hypothesis for the Hausman test. On the other hand, I fail to reject the null for both fixed-weighted and the chain-type user costs. These results suggest that the bias associated with the time-varying weighted user cost inflicts unnecessary endogeneity problems due to the changing weights. More importantly, these results suggest that the affliction can be remedied by using a fixed-weighted or chain-type measure of the user cost.

Table 5.7: Robust, Two-way Fixed Effects OLS

	$UF_{i,t}^{99}$	$UF_{i,t}^{05}$	$UC_{i,t}$
$\Delta U_{i,t}/U_{i,t-1}$			

Continued on Next Page...

Table 5.7 – Continued

	$UF^{99}_{i,t}$	$UF^{05}_{i,t}$	$UC_{i,t}$
α_0	-0.007	-0.021	0.009
	(0.035)	(0.035)	(0.036)
α_1	-0.053	-0.068	-0.043
	(0.044)	(0.043)	(0.046)
α_2	-0.094	-0.117*	-0.079
	(0.066)	(0.064)	(0.064)
α_3	-0.157***	-0.178***	-0.159***
	(0.053)	(0.052)	(0.055)
α_4	-0.060	-0.047	-0.040
	(0.056)	(0.048)	(0.056)
α_5	-0.053	-0.039	-0.071
	(0.049)	(0.044)	(0.053)
α_6	-0.156	-0.129***	-0.145**
	(0.056)	(0.044)	(0.059)
SUM (α)	**-0.579*** **	**-0.599*** **	**-0.529*** **
	(0.153)	**(0.147)**	**(0.157)**
$\Delta S_{f,t}/S_{f,t-1}$			
β_0	0.142***	0.142***	0.141***
	(0.011)	(0.011)	(0.011)
β_1	0.074***	0.075***	0.074***
	(0.008)	(0.008)	(0.008)
β_2	0.031***	0.031***	0.031***
	(0.007)	(0.007)	(0.007)
β_3	0.017**	0.017**	0.017**
	(0.008)	(0.008)	(0.008)
β_4	0.009	0.009	0.009
	(0.006)	(0.006)	(0.006)
SUM (β)	**0.272*** **	**0.272*** **	**0.272*** **
	(0.021)	**(0.021)**	**(0.021)**
$CF_{f,t}/\hat{K}_{f,t-1}$			
γ_0	-0.011***	-0.011***	-0.011***
	(0.004)	(0.004)	(0.004)
γ_1	0.017***	0.017***	0.017***
	(0.003)	(0.003)	(0.003)
γ_2	0.006*	0.006*	0.006*
	(0.003)	(0.004)	(0.003)
γ_3	0.003	0.004	0.003
	(0.004)	(0.004)	(0.005)
γ_4	-0.001	-0.001	-0.001
	(0.002)	(0.003)	(0.003)
SUM (γ)	**0.014***	**0.015***	**0.014***
	(0.007)	**(0.007)**	**(0.007)**
Observations	21,003	21,003	21,003
per group: min	2	2	2
per group: avg	8.6	8.6	8.6
per group: max	16	16	16
Number of firms	2,435	2,435	2,435
Time horizon	1995-2010	1995-2010	1995-2010

Continued on Next Page. . .

Table 5.7 – Continued

	$UF_{i,t}^{99}$	$UF_{i,t}^{05}$	$UC_{i,t}$

Notes: For comparability with the benchmark (Chirinko et al., 1999), standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Given the statistical evidence that the fixed effects OLS estimates are consistent, it is preferrable to use that estimation procedure on the grounds of efficiency. In Table 5.7, I report the results of two-way fixed effects OLS regressions for the two fixed-weighted and chain type user costs, which are robust to arbitrary heteroskedasticity and autocorrelation.[3] These results provide consistent and precise estimates for the user cost elasticity, the sales accelerator and the effect of liquidity constraints on investment. The point estimates for the individual coefficients and their sums are virtually identical for the sales and cash flow variables, so I confine my discussion to the user cost estimates. Although most of the individual coefficient estimates are insignificant, they are almost uniformly negative (the lone exception is the contemporaneous value of the chained user cost), and they are all similar in magnitude. The third lag is always significant at the 1% level, and the sixth lag is significant at least at 5% for the 2005 fixed-weight and the chain-type user costs. The estimates for the user cost elasticity range from -0.579 to -0.529, all are significant at 1%, and none include negative one in their 95% confidence intervals. These results corroborate the findings of Chirinko et al. (2011), who test various investment function estimation techniques on a common panel micro-dataset. First, they note the importance of including time dummies in any micro-data regression for investment. Second, their point estimates of the user cost elasticity on the common panel range from -0.372 to -0.540, all of which include my point estimates in their respective confidence intervals.

In concluding the replication portion of this chapter, I will make a few remarks on what was learned from this exercise. First, using the standard time-varying weighted measure of the user cost likely introduces unnecessary endogeneity issues for estimation. It is quite possible that by using time-varying weights in the user cost, one is identifying some sort of endogeneity in the choice of capital structure. If that is the case, one will not get accurate estimates of how changes in the underlying cost of capital goods affect the level of investment, holding the structure of investment constant. In addition, the bias associated with using the time-varying weighted measure only increases when faced with the rapid decline in computer-based capital assets that was experienced

[3]Two-way fixed effects is essentially a fixed effects estimation with time dummies.

by firms in the nineties and double-oughts. By using a fixed-weighted or chain-type user cost measure, this bias can be eliminated thus allowing for consistent estimation by OLS. Because any fixed-weighted series contains its own bias as one gets farther away from the chosen base year, the chained user cost index should be the preferred measure. Lastly, it is clear that I have a reliable baseline, comparable to existing research, into which I can introduce the real exchange rate.

5.2 Extension: Real Exchange Rates

In this section, I take what was learned from the replication process and investigate the effect of the real exchange rate on investment in U.S. manufacturing firms using a large micro-level dataset. To my knowledge, no such study has been conducted for any sector of the U.S. economy using firm level data. This addition to the literature is in the spirit of the aggregate level analysis by Blecker (2007), who adds the real value of the dollar to a distributed lag model of investment. While Blecker (2007) controlled for accelerator effects, the user cost, and liquidity constraints, he used aggregate, economy-wide data for the entire manufacturing sector and not micro-level data. In this section, I create a baseline by pooling all U.S. manufacturing firms in the dataset. I test whether the real value of the dollar is more likely to affect the rate of investment or the desired capital stock by entering the variable in either levels or difference form, respectively. Then, I investigate how these results may differ when classifying firms by varying degrees and types of international orientation. As will be seen, although I do not find any evidence of significant exchange rate effects in the whole sample of firms, I do find such evidence in many of the split samples for firms in industries with higher degrees of exchange rate exposure by several alternative measures.

5.2.1 Baseline Estimates for All Firms

All of the evidence from the replication section suggests that it is unnecessary to resort to GMM estimation when using the chain-type user cost index. Therefore, I choose to estimate a robust two-way fixed effects OLS model of investment, which uses the chain-type user cost index. A major difference between the industry level analysis of Chapter 4 and the firm level analysis here is that the data used in the extension is the same as that used in the replication. As a result, I extend the distributed lag model of Chirinko et al. (1999) and estimate the following specification for the investment function:

$$\frac{I_{f,t}}{\hat{K}_{f,t-1}} = \phi_t^f + \sum_{h=0}^{a} \alpha_h \left(\frac{\Delta UC_{i,t-h}}{UC_{i,t-h-1}} \right) + \sum_{h=0}^{b} \beta_h \left(\frac{\Delta S_{f,t-h}}{S_{f,t-h-1}} \right) + \sum_{h=0}^{g} \gamma_h \left(\frac{CF_{f,t-h}}{\hat{K}_{f,t-h-1}} \right) + \sum_{h=0}^{l} \lambda_h (e_{i,t-h}) + \nu_f + \epsilon_{f,t} \tag{5.2}$$

where f is a firm index, i is an industry index, t is the time period, and ϕ_t^f is a time-period dummy, which is described in greater detail, below. $I_{f,t}$ is real firm investment, $\hat{K}_{f,t}$ is the real value of the firm's estimated replacement capital stock, $S_{f,t}$ is the firm's real value of sales, and $CF_{f,t}$ is the firm's cash flow. Using my data, the chained user cost of capital, $UC_{i,t}$, is industry-specific, and it is matched to the firm by the two-digit SIC code. The real value of the dollar, $e_{i,t}$, enters the model as an industry-specific real exchange rate index, because the inclusion of time dummies precludes the use of a macro variable such as the broad, trade-weighted real value of the U.S. dollar index. The industry-specific exchange rate is also matched to the firm by two-digit SIC code. No longer constrained by the specification of Chirinko et al. (1999), I leave the lag structure open to empirical investigation with a, b, g and l being the number of lags used for each independent variable.

Estimating a two-way fixed effects model on a large, unbalanced panel presents a peculiar econometric issue in regard to the time-specific effect. For two-way fixed effects estimation, Baum (2006) recommends transforming the time dummies into centered indicators by subtracting the indicator for an excluded class from each of the other indicator variables. This transformation is performed before estimation by fixed effects, which further transforms the data into deviations from the mean. After estimation, the resultant time dummies are then expressed as variations from the conditional mean of the sample. Because of the highly unbalanced nature of my firm level dataset, identifying a single year to be used as the excluded class, which is common to all firms within each regression iteration, becomes problematic if not impossible. Instead, I take a similar approach to that of Arellano and Bond (1991), whereby I construct the time-specific effects so that they become standard time dummies after the mean-deviation transformation of fixed effects regression. As an example, assume $t = 2010$. For those firms in the sample in that year, $\phi_{2010}^f = n_f/(n_f - 1)$, where n_f is the number of observations for each firm. For those same firms, $\phi_t^f = 1/(n_f - 1), \forall t \neq 2010$. In constructing the time dummies this way, it is also much easier to standardize the time effects across split sample regressions.

With the specification of Equation (5.2), the user cost and sales variables enter into the model as growth rates, because they affect the desired capital stock (investment is a change in the capital stock). On the other hand, the cash flow variable enters the model in levels to indicate whether the flow of investment (*i.e.*, the rate at which firms move toward their desired capital stocks) could be financially constrained. As noted previously, it is an empirical question whether the exchange rate variable should enter the investment function in level or difference form. In the industry level analysis of Chapter 4, the theoretical and empirical analyses were based upon the effect of the exchange rate on the desired capital stock, so all variables, including the value of the dollar, were measured in differences. In contrast, the Chirinko et al. (1999) firm level framework allows one more empirical maneuverability when testing for exchange rate effects. In fact, Blecker (2007) finds that the real value of the dollar is more likely to affect investment via the channel of liquidity constraints (*i.e.*, the exchange rate is significant when entered in levels form) in his analysis of U.S. manufacturing using aggregate data. I begin the analysis by setting a baseline regression without the exchange rate and use Bayesian information criteria (BIC) to select the lag structure. I then add the total trade weighted industry-specific real value of the dollar (ter); first in levels form, and then as a growth rate.

Table 5.8. Two-way Fixed Effects OLS, with and without the Exchange Rate

	(1)	(2)	(3)	(4)	(5)
$\Delta UC_{i,t}/UC_{i,t-1}$					
α_0	0.00692	-0.00236	-0.00179	0.00501	0.00506
	(0.18)	(-0.06)	(-0.05)	(0.13)	(0.13)
α_1	-0.0474	-0.0513	-0.0472	-0.0446	-0.0446
	(-1.07)	(-1.19)	(-1.06)	(-0.98)	(-0.98)
α_2	-0.0808	-0.0858	-0.0863	-0.0829	-0.0829
	(-1.23)	(-1.27)	(-1.27)	(-1.25)	(-1.25)
α_3	-0.165***	-0.159***	-0.155***	-0.159***	-0.159***
	(-3.21)	(-3.06)	(-2.94)	(-3.07)	(-3.06)
α_4	-0.0450	-0.0403	-0.0484	-0.0513	-0.0511
	(-0.82)	(-0.76)	(-0.90)	(-0.90)	(-0.89)
α_5	-0.0808	-0.0778	-0.0795	-0.0827	-0.0829
	(-1.58)	(-1.54)	(-1.57)	(-1.60)	(-1.62)
α_6	-0.142**	-0.137**	-0.141**	-0.146**	-0.146**
	(-2.41)	(-2.33)	(-2.42)	(-2.47)	(-2.48)
SUM (α)	**-0.5534*** **	**-0.5540*** **	**-0.5591*** **	**-0.5615*** **	**-0.5615*** **
	(-3.32)	**(-3.32)**	**(-3.35)**	**(-3.33)**	**(-3.33)**
$\Delta S_{f,t}/S_{f,t-1}$					
β_0	0.143***	0.143***	0.143***	0.143***	0.143***

Continued on Next Page. . .

Table 5.8 – Continued

	(1)	(2)	(3)	(4)	(5)
	(12.36)	(12.34)	(12.34)	(12.36)	(12.36)
β_1	0.0756***	0.0754***	0.0754***	0.0756***	0.0756***
	(8.44)	(8.42)	(8.42)	(8.44)	(8.43)
β_2	0.0330***	0.0328***	0.0327***	0.0329***	0.0329***
	(4.13)	(4.10)	(4.10)	(4.12)	(4.12)
β_3	0.0197**	0.0196**	0.0197**	0.0198**	0.0198**
	(2.24)	(2.23)	(2.24)	(2.25)	(2.25)
β_4	0.00951	0.00939	0.00945	0.00953	0.00953
	(1.56)	(1.55)	(1.55)	(1.57)	(1.57)
β_5	0.0171**	0.0170**	0.0171**	0.0171**	0.0171**
	(2.20)	(2.20)	(2.20)	(2.21)	(2.21)
SUM (β)	**0.2976*** **	**0.2967*** **	**0.2969*** **	**0.2976*** **	**0.2976*** **
	(9.95)	**(9.95)**	**(9.95)**	**(9.96)**	**(9.95)**
$CF_{f,t}/\hat{K}_{f,t-1}$					
γ_0	-0.0114**	-0.0114**	-0.0114**	-0.0114**	-0.0114**
	(-2.57)	(-2.57)	(-2.57)	(-2.57)	(-2.57)
γ_1	0.0169***	0.0169***	0.0170***	0.0170***	0.0170***
	(4.66)	(4.66)	(4.67)	(4.67)	(4.67)
γ_2	0.00610*	0.00611*	0.00609*	0.00609*	0.00609*
	(1.78)	(1.78)	(1.78)	(1.78)	(1.78)
γ_3	0.00310	0.00309	0.00307	0.00308	0.00308
	(0.58)	(0.58)	(0.57)	(0.58)	(0.58)
SUM (γ)	**0.01475***	**0.01475***	**0.01472***	**0.01472***	**0.01472***
	(1.82)	**(1.82)**	**(1.81)**	**(1.82)**	**(1.82)**
$ter_{i,t}$					
λ_0		-0.0998	-0.193		
		(-0.94)	(-1.28)		
λ_1			0.121		
			(1.09)		
$\Delta ter_{i,t}/ter_{i,t-1}$					
λ_0				-0.125	-0.125
				(-0.96)	(-0.96)
λ_1					-0.00570
					(-0.04)
SUM (λ)		**-0.0998**	**-0.0723**	**-0.1254**	**-0.1304**
		(-0.94)	**(-0.70)**	**(-0.96)**	**(-0.71)**
Observations	21,193	21,193	21,193	21,193	21,193
per group: min	1	1	1	1	1
per group: avg	8.1	8.1	8.1	8.1	8.1
per group: max	16	16	16	16	16
Number of firms	2,625	2,625	2,625	2,625	2,625
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0619	0.0620	0.0620	0.0620	0.0620
$\hat{\sigma_\nu}$	0.2038	0.2027	0.2029	0.2037	0.2037
$\hat{\sigma_\epsilon}$	0.2679	0.2679	0.2679	0.2679	0.2679
ρ	0.3665	0.3641	0.3646	0.3664	0.3664

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5.8, I present the regression results of two-way fixed effects OLS, which are robust to arbitrary heteroskedasticity and autocorrelation, with and without the different potential measures of the total trade-weighted industry-specific real exchange rate. The results in column (1) reflect the lag structure of the baseline regression according to the minimization of the BIC. In the previous section on replication, the lag structure was determined by an *ad hoc* comparison to previous research. By minimizing the BIC, I arrive at a similar lag structure to that of Chirinko et al. (1999). Using my data, however, the information criteria suggest that six, five and three lags are appropriate for the user cost growth, sales growth and cash flow to capital ratio, respectively. Using this particular lag structure has very little effect on the estimates of the individual coefficients and their sums in terms of sign, magnitude, and significance, when compared to the replication results.

In column (2) of Table 5.8, I present the results for including only the contemporaneous value of the level of the total industry-specific real exchange rate index. According to the BIC, information is lost when including additional lags of the exchange rate. When entered in levels form, the single estimated coefficient for the exchange rate variable is negative but small (-0.0998) and insignificant. In addition, all of the estimated coefficients for the other independent variables are practically unchanged, a result which holds across all of the regressions in Table 5.8. In column (3), I present the results of including a single lag of the exchange rate index in addition to the contemporaneous value to provide an example of what happens when adding additional lags. The coefficient for the contemporaneous value is negative and greater in absolute value, but it is offset by the positive coefficient for the first lag, and both are insignificant. The resultant sum yields an estimate that is similar to the estimate for including only the contemporaneous value. The results of including the value of the dollar in levels form suggest that the exchange rate has no effect on U.S. manufacturing firm investment through the channel of liquidity constraints. This result is in stark contrast to the significant negative effect found by Blecker (2007) for the aggregate manufacturing sector.

To test whether the exchange rate affects the desired capital stock, I include the rate of appreciation instead of the level of the dollar, the results of which are presented in column (4). Again, the BIC suggest that only the contemporaneous value of the exchange rate should be included. The estimated coefficient, while negative and a bit larger in absolute value than the one for the levels form, is still insignificant. In column (5), I demonstrate that including a lagged value has no impact on the overall results. The results of including the exchange rate variable in growth form also suggest that the exchange rate has no effect on U.S. manufacturing firm investment through a possible effect on desired capital stocks. This result is in stark contrast to the strong, overall negative effect that I repeatedly found in the industry level analysis of Chapter 4. Although not reported here, I find qualitatively similar results when including the export-weighted industry exchange rate index (xer) or the import-weighted industry exchange rate index (mer) in the same specification as above.

5.2.2 Exchange Rate Exposure

Table 5.9. Sample Splits by International Exposure, According to Primary Industry Classification.

SIC	Industry name	Export Share, χ		Imported Input Share, α		Import Share, m		Average Number of Firms
Nondurables:								
20	Food		Low		Low		Low	92.88
21	Tobacco	High			Low		Low	4.20
22	Textiles		Low		Low	High		26.84
23	Apparel		Low		Low	High		40.52
24	Lumber and wood		Low		Low		Low	26.77
25	Furniture, fixtures	High		High		High		28.41
26	Paper and allied		Low		Low		Low	40.87
27	Printing, publishing		Low		Low		Low	51.82
28	Chemicals	High		High			Low	307.37
29	Petroleum and coal		Low		Low		Low	22.05
Durables:								
30	Rubber and misc.		Low		Low		Low	51.40
31	Leather	High		High		High		14.11
32	Stone, clay, glass		Low		Low		Low	28.38
33	Primary metals	High		High		High		62.31
34	Fabricated metals		Low	High			Low	67.00
35	Industrial machines	High		High		High		242.84
36	Electronic, electric	High		High		High		324.05
37	Transportation	High		High		High		97.04
38	Instruments	High		High		High		275.23
39	Other mfg.	High		High		High		44.74
Average number of firms		1392.32	444.80	1453.24	381.98	1149.18	682.40	

Source: Author's calculations based on data presented in Chapter 3.

The fact that I find no evidence of exchange rate effects on investment in the full sample of U.S. manufacturing firms could be due to the pooling of firms with varying degrees or types of international exposure. Given this possibility, I create sub-samples of firms that reflect different channels of exchange rate exposure. It would be better if I could classify the firms using exposure data at the firm level, but that data is often not available or incomplete in Compustat. Instead, I utilize the detailed exposure data from the industry level analysis by matching the firm to an industry based upon its primary SIC. I then split the sample by identifying firms with different degrees of exchange rate exposure, using the three measures of external orientation described in Chapter 3: export share, χ, imported input share, α, and import penetration, m. I compare the industry's average value for each measure to the median of the average values for all industries, in order to define the sample splits.[4]

In Table 5.9, I present the industry level sample splits by international exposure and the average number of firms that fall within each category. In classifying firms by exposure to export markets, I find that the publicly-traded firms included in Compustat tend to operate primarily in the industries with a higher reliance on export sales. The average number of firms in industries with a higher relative export share is 1392.32, compared to 444.80 for the lower export share industries. By splitting the sample by industry reliance on the use of imported manufactured intermediate goods, I find that publicly-traded firms also tend to operate primarily in the industries with a higher imported input share. The average number of firms in industries with a higher relative imported input share is 1453.24, compared to 381.98 for the lower imported input share industries. In addition, there is a high degree of overlap between the sample splits by export share and imported input share. All of the industries except tobacco and fabricated metals carry the same classification. In other words, it appears that publicly-traded firms may be more likely to operate primarily in those industries with greater exposure to exchange rates from export sales and imported inputs.

To a lesser degree, I also find that more of the publicly-traded firms in the sample tend to operate primarily in industries facing a higher level of import penetration, with 1149.18 classified as high import share and 682.40 classified as low import share on average. Again, there is a substantial amount of overlap in the samples that are split by the different measures of external orientation. Eight industries are classified as having high exposure through all three exchange rate channels (furniture and fixtures, leather, primary metals, industrial machinery, electronic and other electric products, transportation, instruments and other manufacturing), and, seven are classified as having low exposure through all three channels (food and kindred, lumber and wood, paper and allied, printing and publishing, petroleum and coal, rubber and miscellaneous, and stone, clay and glass).

Table 5.10. Two-way FE OLS: High Export Share Industries

		ter		*xer*	
	(1)	(2)	(3)	(4)	(5)
$\Delta UC_{i,t}/UC_{i,t-1}$					
$\sum_{h=0}^{6}\alpha_h$	-0.5465**	-0.5407**	-0.5460**	-0.5412**	-0.5598**
	(-2.46)	(-2.51)	(-2.46)	(-2.45)	(-2.48)
$\Delta S_{f,t}/S_{f,t-1}$					
$\sum_{h=0}^{5}\beta_h$	0.3456***	0.3441***	0.3452***	0.3442***	0.3455***
	(11.30)	(11.22)	(11.32)	(11.24)	(11.31)
$CF_{f,t}/\hat{K}_{f,t-1}$					
$\sum_{h=0}^{3}\gamma_h$	0.0109	0.0109	0.0109	0.0110	0.0109
	(1.33)	(1.33)	(1.32)	(1.33)	(1.32)
$e_{i,t}$		-0.1525		-0.2141	
		(-1.05)		(-1.26)	
$\Delta e_{i,t}/e_{i,t-1}$			-0.3356*		-0.3668
			(-1.83)		(-1.56)
Observations	15,930	15,930	15,930	15,930	15,575
Number of firms	1,992	1,992	1,992	1,992	1,955
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0752	0.0754	0.0755	0.0754	0.0755
$\hat{\sigma_\nu}$	0.2012	0.1998	0.2010	0.1999	0.2018
$\hat{\sigma_\epsilon}$	0.2743	0.2743	0.2743	0.2743	0.2770
ρ	0.3497	0.3466	0.3493	0.3469	0.3469

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2.3 Exposure by Export Share

In the industry level analysis of Chapter 4, an important conclusion is that the exchange rate tends to affect investment decisions mainly through its impact on competitiveness in export markets (the export channel). Surprisingly, including the export-weighted, industry-specific exchange on the full sample of firms yielded no statistically significant effect on investment. As an alternative, I attempt to pinpoint the export channel at the firm level by testing the effect of the exchange rate on investment for the sub-sample of firms whose primary SIC corresponds to an industry with a relatively high share of export revenues.

In Table 5.10, I present the results of robust, two-way fixed effects OLS estimates for those firms whose primary industry is classified as having a relativly high degree of exchange rate exposure in export markets. I test the exchange rate effect in levels and growth rates, using both the total

[4] Because the industry level data covers 1973-2005 and the firm level data covers 1987-2010, I do my best to align the time periods by creating the industry classifications using the industry level data from 1987 to 2005.

trade weighted and the export-weighted industry-specific exchange rate indexes. In column (1), I present the estimated coefficient sums for the baseline regression without an exchange rate variable. Minimization of the BIC suggests that the lag structure remains the same as for the full sample. The estimated coefficient sums for the user cost and accelerator are similar to those of the full sample in terms of sign, magnitude, and level of significance. On the other hand, the estimated coefficient sum for the cash flow variable, although positive and similar in magnitude to the full sample result, is now insignificant, which suggests that firms in more export-oriented industries may be less likely to suffer from liquidity constraints than those in less export-oriented industries. In support of my earlier assertion that large, publicly traded firms are more likely to have a larger presence in export markets, just over 75% (1,992 out of 2,625) of the firms remain in the sample, when split by export share.

In columns (2) and (3) of Table 5.10, I introduce the total trade weighted industry-specific exchange rate (ter) in levels form and growth rate, respectively. Again, using the BIC suggests that only the contemporaneous value of the exchange rate should be included for either specification. First, one should note that the estimated sums of the coefficients for the user cost, accelerator and cash flow variables are practically unchanged when introducing the exchange rate. When the total trade industry-specific exchange rate is entered in levels, its coefficient remains negative and insignificant. When it is entered as a growth rate the coefficient is negative and significant, but only at 10%. In addition, the magnitude of the estimated coefficient at -0.3356 suggests that the effect of the exchange rate on the desired capital stock is on par with that of the user cost elasticity and accelerator effect for firms in high export-oriented industries. However, when the export-weighted industry-specific exchange rate (xer) is entered either in levels form or growth rate (columns (4) and (5), respectively), the estimated coefficients, although negative, are statistically insignificant.

Overall, for those firms whose primary SIC indicates that they operate in a more export-oriented industry, I find that the effect of the user cost and accelerator on investment are similar to those of all U.S. manufacturing firms as a whole. In contrast to the full sample, I find that investment by these firms is not constrained due to cash flow. I also find no evidence of liquidity constraints due to real exchange rate valuation. On the other hand, there is some evidence that these firms adjust their desired capital stock in response to a real dollar appreciation/depreciation, when the real value of the dollar is weighted by total industry trade. In this case, a real dollar appreciation would have a large and significant negative effect on investment.

Table 5.11. Two-way FE OLS: Low Export Share Industries

		ter		*xer*	
	(1)	(2)	(3)	(4)	(5)
$\Delta UC_{i,t}/UC_{i,t-1}$					
$\sum_{h=0}^{6}\alpha_h$	-0.7037***	-0.6585***	-0.6704***	-0.7107***	-0.7541***
	(-3.69)	(-3.35)	(-3.35)	(-3.74)	(-3.78)
$\Delta S_{f,t}/S_{f,t-1}$	0.1109***	0.1111***	0.1107***	0.1107***	0.1109***
	(2.81)	(2.81)	(2.82)	(2.81)	(2.81)
$CF_{f,t}/\hat{K}_{f,t-1}$					
$\sum_{h=0}^{3}\gamma_h$	0.0878***	0.0875***	0.0879***	0.0878***	0.0876***
	(3.03)	(3.02)	(3.03)	(3.02)	(3.03)
$e_{i,t}$		0.1749		-0.0434	
		(1.31)		(-0.44)	
$\Delta e_{i,t}/e_{i,t-1}$			0.1234		-0.1598
			(0.63)		(-0.80)
Observations	5,263	5,263	5,263	5,623	5,623
Number of firms	633	633	633	633	633
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0471	0.0474	0.0472	0.0472	0.0473
$\hat{\sigma_\nu}$	0.1987	0.2008	0.1987	0.1984	0.1993
$\hat{\sigma_\epsilon}$	0.2435	0.2435	0.2435	0.2435	0.2435
ρ	0.3997	0.4047	0.3997	0.3990	0.4012

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5.11, I present the results for those firms whose primary SIC indicates that they operate in an industry with a lower reliance on exports as a share of revenues. Only 633 firms from the full sample regressions fall within this classification, which suggests that privately owned firms are more likely to operate in these industries, or possibly that these industries are either smaller or more concentrated. For the baseline regression without the exchange rate, which is reported in column (1), the BIC suggests that only the contemporaneous value of sales growth should be included in the estimation equation.[5] In the industry level analysis of Chapter 4, there was some limited evidence that the accelerator effect could be magnified or dampened based upon the level and type of competetion facing an industry. The firm level, distributed lag model used here can provide additional insight into how the accelerator effect can differ between firms that operate in different competetive spheres.

[5] Although not reported, including additional lags of sales growth yielded mostly very small, negative and insignificant coefficients for those lags. Including lags three or greater yielded positive but insignificant sums for the overall accelerator effect.

First, one should note that the estimated coefficient sum for the user cost elasticity is relatively similar in terms of sign, magnitude and significance to both the full sample of firms and those which primarily operate in more export reliant industries. For the firms that operate in less export-reliant industries, however, I find that the effect of current sales growth on investment is relatively similar to that of all manufacturing firms (0.1109 compared to 0.1430 for all firms), but that any additional effect from previous years' sales growth on the accelerator is non-existent. In this case, not only is the overall accelerator effect dampened (0.1109 compared to a sum of 0.2976 for all firms), but also the duration of the accelerator effect is reduced for these firms. One explanation for this change in the accelerator effect is that most of the low export share industries also tend to be in the nondurable goods sector. Table 5.9 shows that seven of the ten nondurable industries also display a relatively lower reliance on export markets. In addition, the positive and highly significant coefficient sum for the cash flow variable suggests that these firms' investment is financially constrained.

In columns (2) and (3) of Table 5.11, I introduce the total trade weighted industry-specific exchange rate (ter) in levels form and growth rate, respectively. Again, using the BIC suggests that only the contemporaneous value of the exchange rate should be included for either specification. The estimated sums for the user cost, accelerator and cash flow variables are practically unchanged when introducing the exchange rate. When the total industry-specific exchange rate is included in either level or growth rate form, its coefficient is positive and insignificant. In a similar manner, I introduce the export-weighted exchange rate (xer) in columns (4) and (5) and find negative and insignificant coefficient estimates for the real value of the dollar using this measure.

So, although the firms that operate in more export reliant industries show a significant, negative, total trade weighted exchange rate effect operating via the desired capital stock, those firms that operate in less export reliant industries show no impact of the exchange rate on investment through either the desired capital stock or liquidity constraints. In addition, for the firms in export-oriented industries, the estimated total trade weighted real exchange rate effect (-0.3356) is similar in order of magnitude to my preferred estimate (-0.508 for Δter) for all U.S. manufacturing industries in Chapter 4.

5.2.4 Exposure by Imported Input Share

Next, I present the results of robust, two-way fixed effects OLS estimates for sub-samples of firms that are divided by industries according to their reliance on imported intermediate goods. Again, I test the exchange rate effect in levels and growth rates, but this time using the total and import-weighted industry-specific exchange rates. According to Campa and Goldberg (1995, 1999), one might expect to find a positive exchange rate effect on investment through its effect on the cost of imported intermediaries (the cost channel).

Table 5.12. Two-way FE OLS: High Imported Input Share Industries

		ter		*mer*	
	(1)	(2)	(3)	(4)	(5)
$\Delta UC_{i,t}/UC_{i,t-1}$					
$\sum_{h=0}^{6}\alpha_h$	-0.5131**	-0.5037**	-0.5116**	-0.5092**	-0.5064**
	(-3.03)	(-2.32)	(-2.34)	(-2.33)	(-2.32)
$\Delta S_{f,t}/S_{f,t-1}$					
$\sum_{h=0}^{5}\beta_h$	0.3438***	0.3421***	0.3434***	0.3427***	0.3434***
	(11.46)	(11.36)	(11.47)	(11.38)	(11.47)
$CF_{f,t}/\hat{K}_{f,t-1}$					
$\sum_{h=0}^{2}\gamma_h$	0.0083	0.0083	0.0082	0.0083	0.0082
	(1.20)	(1.20)	(1.19)	(1.20)	(1.19)
$e_{i,t}$		-0.1613		-0.0808	
		(-1.12)		(-0.85)	
$\Delta e_{i,t}/e_{i,t-1}$			-0.3192*		-0.2302*
			(-1.79)		(-1.85)
Observations	16,664	16,664	16,664	16,664	16,664
Number of firms	2,081	2,081	2,081	2,081	2,081
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0754	0.0756	0.0757	0.0757	0.0757
$\hat{\sigma_\nu}$	0.1979	0.1964	0.1977	0.1965	0.1977
$\hat{\sigma_\epsilon}$	0.2700	0.2700	0.2699	0.2699	0.2699
ρ	0.3495	0.3462	0.3492	0.3464	0.3492

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In column (1) of Table 5.12, I present the estimated coefficient sums for the baseline regression without an exchange rate variable for the firms whose primary industry is classified as using a higher share of imported intermediate goods. Minimization of the BIC suggests that the lag structure for the user cost and accelerator remains the same as for the full sample, but that cash flow should be reduced to lags zero through two. The estimated coefficient sums for the user cost and accelerator are similar to those of the full sample in terms of sign, magnitude and level of significance. On the other hand, the estimated coefficient sum on the cash flow variable, although positive, is very small and insignificant. In support of my earlier assertion that the large, publicly traded firms in this sample are more likely to rely on imported intermediate goods, 79% (2,081 out of 2,625) of the firms remain from the full sample.

In columns (2) and (3) of Table 5.12, I introduce the total trade weighted industry-specific exchange rate index (*ter*) in levels form and growth rate, respectively. Again, using the BIC suggests that only the contemporaneous value of the exchange rate should be included for either specification; and the estimated sums for the user cost, accelerator, and cash flow variables are practically unchanged when introducing the exchange rate. When the total industry-specific exchange rate is included in levels, its coefficient is negative and insignificant. When it is entered in growth rate form, however, the coefficient (-0.294) is negative, significant at 10%, and similar to the magnitude found for the firms in high export-oriented industries. This result is not too surprising due to the large overlap between the samples split by export share and imported input share (nine of the ten high imported input share industries are also classified as having a higher export share), but it does suggest that the intermediate import cost factor does not outweigh the negative effects of an appreciating dollar on the competitiveness of a firm, even when a firm relies heavily on imported inputs.

Interestingly, a similar pattern of results arises in columns (4) and (5) when the import-weighted industry-specific exchange rate (*mer*) is entered in either levels or growth rate form, with a similar sized coefficient (-0.2302) for the exchange rate change that is significant at 10%. Again, there is considerable overlap between the samples split by import penetration and imported input share (eight of the ten high imported input share industries are also classified as having higher import penetration). So, although these firms operate primarily in industries with a higher amount of positive exposure to the value of the real dollar through their reliance on imported intermediaries, the results suggest that they experience a net negative effect of an appreciating dollar on investment via the desired capital stock, even when the exchange rate is weighted by total industry imports.[6]

Overall, I find that firms operating primarily in industries using a higher share of imported intermediate goods also have significant exchange rate exposure in export markets and/or through competition with imported final goods. In addition, the results presented in Table 5.12 suggest that an appreciating dollar reduces these firms' desired capital stock, even though they tend to import a larger share of their manufactured intermediate goods. It appears that the negative effect of the exchange rate on investment due to competing imports that tends to outweigh any positive effect of the exchange rate on imported input costs.

---

[6]Although not reported in the table; if I include the export-weighted exchange rate, the estimated exchange rate coefficients, while negative, are statistically insignificant (-0.2244 for levels and -0.3032 for growth).

Overall, the firm level results presented so far tend to identify a negative effect of the real exchange rate on the desired capital stock of publicly traded firms whose primary operations are in industries with relatively high exchange rate exposure in export markets and to the cost of imported intermediate goods.

Table 5.13. Two-way FE OLS: Low Imported Input Share Industries

			ter		*mer*
	(1)	(2)	(3)	(4)	(5)
$\Delta UC_{i,t}/UC_{i,t-1}$					
$\sum_{h=0}^{6}\alpha_h$	-0.7604***	-0.7148***	-0.7376***	-0.6691***	-0.6929***
	(-4.04)	(-3.69)	(-3.76)	(-3.35)	(-3.59)
$\Delta S_{f,t}/S_{f,t-1}$	0.1150**	0.1153**	0.1148**	0.1146**	0.1143**
	(2.42)	(2.42)	(2.42)	(2.42)	(2.41)
$CF_{f,t}/\hat{K}_{f,t-1}$					
$\sum_{h=0}^{3}\gamma_h$	0.0858***	0.0854***	0.0859***	0.0845***	0.0857***
	(2.87)	(2.87)	(2.87)	(2.85)	(2.86)
$e_{i,t}$		0.1945		0.3095**	
		(1.50)		(2.04)	
$\Delta e_{i,t}/e_{i,t-1}$			0.0843		0.2825**
			(0.46)		(2.11)
Observations	4,529	4,529	4,529	4,529	4,529
Number of firms	544	544	544	544	544
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0434	0.0438	0.0435	0.0447	0.0416
$\hat{\sigma_\nu}$	0.2106	0.2129	0.2106	0.2162	0.2344
$\hat{\sigma_\epsilon}$	0.2559	0.2559	0.2559	0.2557	0.2776
ρ	0.4038	0.4090	0.4038	0.4169	0.4164

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.13 presents the results for those firms whose primary SIC indicates that they operate in an industry with a lower reliance on imported intermediate goods. Only 544 firms from the full sample regressions fall within this classification, which, as in the low export share split, suggests that privately owned firms are more likely to operate in these industries. Also as in the less export-oriented industries, the BIC suggests that only the contemporaneous value of sales growth should be included in the baseline estimation equation.[7] Again, there is significant overlap between the low export share industries and the low imported input industries.

[7] Although not reported, I found no evidence that the change in the number of lags for the accelerator was due to small sample splits. I randomly selected a group of 700 firms from the full sample (seed=19721205), which resulted in 3,816 observations and 479 firms used in the regression. All of the individual coefficients were relatively unchanged from the full sample estimation and the BIC suggested five lags for the accelerator.

The sign, magnitude, and significance of the estimated coefficients in the baseline regression reported in column (1) are similar to the coefficient estimates for the less export-oriented industries. The change in lag structure suggests that the duration of the accelerator effect is shortened for these firms as well. In addition, the positive and highly significant coefficient sum for the cash flow variable suggests that these firms' investment is financially constrained. In columns (2) and (3) of Table 5.13, I introduce the total industry-specific exchange rate (ter) in levels form and growth rate, respectively. Minimization of the BIC suggests that only the contemporaneous value of the exchange rate should be included for either specification. First, one should note that the estimated sums for the user cost, accelerator and cash flow variables are relatively unchanged when introducing the exchange rate. When the total trade weighted industry-specific exchange rate is included in either level or growth rate form, its coefficient is positive and insignificant.

In column (4), I introduce the import-weighted exchange rate (mer) in levels form, which yields a positive exchange rate coefficient of 0.3095 that is significant at 5%. This is the first time that the exchange rate yields a significant coefficient that is positive and seems to affect investment through the channel of liquidity constraints. Before trying to untangle this puzzle, however, the results in column (5) show that the estimated exchange rate coefficient on the change in the import-weighted exchange rate (0.2825) is similar in magnitude and significance, which now suggests a positive effect of the exchange rate on the desired capital stock. These results are puzzling, indeed.

First, I address the fact that all of the estimated exchange rate coefficients in this sub-sample are consistently positive and of similar order of magnitude. Since the sample includes only those firms that operate in industries with a lower reliance on imported intermediaries, this result is surprising. First, the overlap in the sample splits indicates that the low imported input industries also tend to have less exchange rate exposure in export markets and from competing imports. So, many of these firms have less negative exposure to the real value of the dollar relative to their peers in the high imported input sub-sample. To the extent that these firms rely on imported intermediaries at all, the lesser degree of negative exposure to the real value of the dollar could enable the positive cost channel effect to show up in the results.

At the same time, the positive coefficients are only significant when including the import-weighted exchange rate. Recall, this measure of the exchange rate is industry-specific, and the weights are determined by the imports of all goods (both competing final goods and intermediate goods) into the domestic industry. If these firms tend to rely heavily on intra-industry intermediate goods, then it is possible that the exchange rate may have a significant effect on input costs.

Referring to Table 5.9, one finds that the low imported input share industries include food, tobacco, textiles, apparel, lumber and wood, paper and allied, printing and publishing, petroleum and coal, rubber, and stone, clay, and glass. Given the broad industry classifications at the two-digit SIC level, these firms could likely rely heavily on intra-industry intermediate goods.

Disentangling whether this positive exchange rate effect works through the channel of liquidity constraints, the desired capitals stock, or both, becomes tricky. Thus far, all other significant exchange rate coefficients have suggested that the exchange rate affects a firm's desired capital stock. The positive and significant coefficient on the change in the real value of the dollar in this sub-sample supports those previous findings. In such a case, an appreciating import-weighted dollar may induce the firms in this sample to increase their desired capital due to the falling prices of imported inputs. On the other hand, the estimated coefficient on the level of the real value of the dollar measured by *mer* is also positive and significant. In this case, given a particular level of cash flow, sales growth and user cost growth, a higher real value of the dollar (when weighted by imports) may ease the barriers to investment created by cash flow type liquidity constraints.

5.2.5 Exposure by Import Penetration

Next, I present the results of robust, two-way fixed effects OLS estimates for sub-samples of firms that are divided by industries according to the degree of import penetration in the domestic market. Again, I test the exchange rate effect in levels and growth rates, using the total trade weighted and the import-weighted industry-specific exchange rates.

In column (1) of Table 5.14, I present the estimated coefficient sums for the baseline regression without an exchange rate variable for the firms whose primary industry is classified as having a higher share of import penetration. Minimization of the BIC suggests that the lag structure for the user cost and accelerator remains the same as for the full sample, but that cash flow should be reduced to lags zero through two. The estimated coefficient sums for the user cost, accelerator, and cash flow are similar to those of the full sample in terms of sign, magnitude and level of significance. Dividing the sample by industry level of import competition yields a more even division of the data, as only 63% (1,645 out of 2,625) of the firms remain from the full sample.

In columns (2) and (3) of Table 5.14, I introduce the total trade weighted industry-specific exchange rate (*ter*) in levels form and growth rate, respectively. Again, using the BIC suggests that only the contemporaneous value of the exchange rate should be included for either specification, and the estimated sums for the user cost, accelerator and cash flow variables are practically unchanged

Table 5.14. Two-way FE OLS: High Import Penetration Industries

		ter		*mer*	
	(1)	(2)	(3)	(4)	(5)
$\Delta UC_{i,t}/UC_{i,t-1}$					
$\sum_{h=0}^{6}\alpha_h$	-0.5743***	-0.5161**	-0.5731***	-0.5734***	-0.5739***
	(-2.70)	(-2.53)	(-2.71)	(-2.70)	(-2.71)
$\Delta S_{f,t}/S_{f,t-1}$					
$\sum_{h=0}^{5}\beta_h$	0.3877***	0.3846***	0.3877***	0.3853***	0.3877***
	(11.41)	(11.33)	(11.41)	(11.35)	(11.41)
$CF_{f,t}/\hat{K}_{f,t-1}$					
$\sum_{h=0}^{2}\gamma_h$	0.0161*	0.0161*	0.0161*	0.0162*	0.0161*
	(1.71)	(1.71)	(1.71)	(1.71)	(1.71)
$e_{i,t}$		-0.3204**		-0.2455**	
		(-2.17)		(-2.26)	
$\Delta e_{i,t}/e_{i,t-1}$			-0.0374		-0.0113
			(-0.23)		(-0.09)
Observations	13,466	13,466	13,466	13,466	13,466
Number of firms	1,645	1,645	1,645	1,645	1,645
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0836	0.0842	0.0836	0.0841	0.0836
$\hat{\sigma_\nu}$	0.1836	0.1813	0.1836	0.1811	0.1836
$\hat{\sigma_\epsilon}$	0.2616	0.2615	0.2616	0.2615	0.2616
ρ	0.3303	0.3246	0.3300	0.3241	0.3300

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

after introducing the exchange rate. When *ter* is included in levels, its estimated coefficient (-0.3204) is negative, significant at 5%, and a similar order of magnitude to previous results. When it is included as a growth rate, however, the coefficient (-0.055), although negative, is insignificant and very small in magnitude. A similar pattern of results arises in columns (4) and (5) when the import-weighted industry-specific exchange rate (*mer*) is introduced in levels form and growth rate, with a similar sized coeffcient (-0.2455) for the level of the exchange rate that is significant at 5%.

The results in Table 5.14 suggest that firms that operate primarily in industries with a higher level of import competition experience a significant negative effect on investment due to an exchange rate effect through the channel of financial constraints. In addition, the magnitude of this effect is on par with that of the sales accelerator and user cost elasticity. So for these firms, a higher real value of the dollar suggests that investment may be constrained for a given value of user cost growth, sales growth, and cash flow.

Table 5.15. Two-way FE OLS: Low Import Penetration Industries

			ter		*mer*
	(1)	(2)	(3)	(4)	(5)
$\Delta UC_{i,t}/UC_{i,t-1}$					
$\sum_{h=0}^{6} \alpha_h$	-0.7904***	-0.7621**	-0.8726***	-0.6850**	-0.8064***
	(-2.78)	(-2.59)	(-3.20)	(-2.49)	(-3.07)
$\Delta S_{f,t}/S_{f,t-1}$					
$\sum_{h=0}^{1} \beta_h$	0.1416***	0.1414***	0.1419***	0.1410***	0.1417***
	(5.76)	(5.75)	(5.78)	(5.75)	(5.77)
$CF_{f,t}/\hat{K}_{f,t-1}$					
$\sum_{h=0}^{1} \gamma_h$	-0.0012	-0.0012	-0.0012	-0.0012	-0.0012
	(-0.13)	(-0.13)	(-0.13)	(-0.13)	(-0.13)
$e_{i,t}$		0.1305		0.1858	
		(1.00)		(1.62)	
$\Delta e_{i,t}/e_{i,t-1}$			-0.2380		-0.0437
			(-1.15)		(-0.20)
Observations	7,727	7,727	7,727	7,727	7,727
Number of firms	980	980	980	980	980
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0390	0.0391	0.0391	0.0393	0.0390
$\hat{\sigma_\nu}$	0.2253	0.2267	0.2251	0.2281	0.2252
$\hat{\sigma_\epsilon}$	0.2773	0.2773	0.2773	0.2773	0.2773
ρ	0.3977	0.4006	0.3972	0.4037	0.3974

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5.15, I present the results for those firms whose primary industry is classified as having a lower share of import penetration in the domestic market for final goods. Again, I test the exchange rate effect in levels and growth rates, using the total trade weighted and the import-weighted industry-specific exchange rates. Like the less export-oriented and less imported input reliant industries, the BIC suggests that the duration of the accelerator is shortened for the baseline estimation equation, with only the contemporaneous value and the first lag included. The estimated coefficient for the sales accelerator (0.1416) reflects the shortened duration and is significant at 1%. The estimated coefficient sum for the user cost elasticity is similar to those of the low export share and low imported input share sub-samples in terms of sign, magnitude and significance, but the cash flow estimate is negative (practically zero) and insignificant with the BIC suggesting only lags zero to one.

In columns (2) and (3) of Table 5.15, I introduce the total industry-specific exchange rate (*ter*) in levels form and growth rate, respectively. Again, using the BIC suggests that only the contemporaneous value of the exchange rate should be included for either specification. First, one should note that the estimated sums for the user cost, accelerator and cash flow variables are relatively unchanged after introducing the exchange rate. In levels form the estimated exchange rate coefficient (0.1305) is positive but insignificant; while in growth form (-0.2380), it is negative and insignificant. A similar pattern emerges in columns (4) and (5) when the import-weighted exchange rate (mer) is introduced in levels form and growth rate, respectively.

So, although the firms that operate primarily in industries with a higher degree of import penetration show a significant, negative, exchange rate effect operating via liquidity constraints, those firms that operate in industries with a lesser degree of import penetration show no impact of the exchange rate on investment through either the desired capital stock or liquidity constraints. In addition, for the firms facing a higher degree of import competition in the domestic market, the magnitude of the real exchange rate effect (-0.3204 for ter and -0.2455 for mer) is of a similar magnitude to the effects of user cost and sales growth.

At this point, I note that the firm level results presented so far suggest that the effect of the exchange rate on investment for publicly traded U.S. manufacturing firms is highly dependent on the type and degree of international exposure. In addition, the channel through which the exchange rate operates (via the desired capital stock or liquidity constraints) is also sensitive to different classifications of exposure. The only evidence of a significant positive effect of the exchange rate on investment due to lower input costs arises, paradoxically, in the firms that primarily operate in industries that are relatively less reliant on imported intermediaries. But, these firms also tend to have lesser overall negative exchange rate exposure in export markets and from competing imports, so the positive import-weighted exchange rate effect may emerge due to their usage of intra-industry imported inputs. In addition, this cost channel effect shows evidence of affecting the investment decision through both the desired capital stock and liquidity constraints.

On the other hand, there is substantial evidence suggesting an overall negative effect of the exchange rate on investment for the firms who primarily operate in industries that are classified as a having a higher degree of exchange rate exposure. The firms operating primarily in industries that are more reliant on export sales or imported intermediate goods show evidence of an overall negative effect of the exchange rate on investment via the desired capital capital stock, while the firms operating primarily in industries facing a higher degree of import competition show evidence of an overall negative effect via the channel of liquidity constraints. In addition, the negative exchange rate effects are only found to be statistically significant when the real value of the dollar is weighted by total industry trade or imports.

5.2.6 Overall Exchange Rate Exposure

Because there is substantial overlap in the previous sample splits, I create two additional sub-samples based upon the degree of overall international exposure. If a firm operates primarily in an industry with a high export share, high imported input share, and high import share, then it is classified as having high overall exchange rate exposure. Eight industries meet the criteria for high overall exposure: furniture and fixtures, leather, primary metals, industrial machinery, electronic and electric products, transportation equipment, instruments, and other manufacturing. In contrast, if a firm operates primarily in an industry with a low export share, low imported input share and low import share, then it is classified as having low overall exchange rate exposure. Seven industries meet the criteria for low overall exposure: food, lumber and wood, paper and allied, printing and publishing, petroleum and coal, rubber, and stone, clay, and glass. The five industries that are not accounted for in either of the two sub-samples are tobacco, chemicals, textiles, apparel and fabricated metals.

In Table 5.16, I present the results of robust, two-way fixed effects OLS estimates for those firms whose primary industry is classified as having a higher degree of overall exchange rate exposure. In column (1), I present the estimated coefficient sums for the baseline regression without an exchange rate variable. Minimization of the BIC suggests that the lag structure for the user cost and accelerator remains the same as for the full sample, but that cash flow should be reduced to lags zero through two. The estimated coefficient sums for the user cost and accelerator are similar to those of the full sample in terms of sign, magnitude and level of significance. On the other hand, the estimated coefficient sum on the cash flow variable, though positive and similar in magnitude, is insignificant. The number of firms in this sub-sample (1,551) accounts for 59% of the firms in the full sample.

For this sub-sample, I test the exchange rate effect in levels and growth rates, using all three measures of the industry-specific real exchange rate. In columns (2) and (3) of Table 5.16, I introduce the total trade weighted industry-specific exchange rate (ter) in levels form and growth rate, respectively. Again, using the BIC suggests that only the contemporaneous value of the exchange rate should be included for either specification, and the estimated sums for the user cost, accelerator and cash flow variables are practically unchanged after introducing the exchange rate.

Table 5.16. Two-way FE OLS: High Overall Exchange Rate Exposure

		ter		*xer*		*mer*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta UC_{i,t}/UC_{i,t-1}$							
$\sum_{h=0}^{6} \alpha_h$	-0.5831***	-0.5386**	-0.5796***	-0.5155**	-0.5911***	-0.5699**	-0.5778***
	(-2.62)	(-2.51)	(-2.62)	(-2.46)	(-2.63)	(-2.59)	(-2.62)
$\Delta S_{f,t}/S_{f,t-1}$							
$\sum_{h=0}^{5} \beta_h$	0.3972***	0.3936***	0.3975***	0.3937***	0.3976***	0.3948***	0.3973***
	(11.45)	(11.34)	(11.46)	(11.35)	(11.46)	(11.38)	(11.45)
$CF_{f,t}/\hat{K}_{f,t-1}$							
$\sum_{h=0}^{2} \gamma_h$	0.0153	0.0153	0.0153	0.0153	0.0153	0.0153	0.0153
	(1.59)	(1.59)	(1.58)	(1.59)	(1.58)	(1.59)	(1.58)
$e_{i,t}$		-0.3727**		-0.3654*		-0.2528**	
		(-2.18)		(-1.94)		(-2.23)	
$\Delta e_{i,t}/e_{i,t-1}$			-0.1831		-0.3029		-0.0821
			(-0.90)		(-1.18)		(-0.61)
Observations	12,699	12,699	12,699	12,699	12,699	12,699	12,699
Number of firms	1,551	1,551	1,551	1,551	1,551	1,551	1,551
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0843	0.0850	0.0843	0.0849	0.0844	0.0848	0.0843
$\hat{\sigma_\nu}$	0.1857	0.1833	0.1856	0.1840	0.1856	0.1831	0.1856
$\hat{\sigma_\epsilon}$	0.2659	0.2659	0.2659	0.2658	0.2659	0.2658	0.2659
ρ	0.3278	0.3221	0.3276	0.3240	0.3276	0.3216	0.3276

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

When the total trade weighted industry-specific exchange rate is included in levels, its estimated coefficient (-0.3727) is negative, significant at 5%, and a similar order of magnitude to previous results. When it is included as a growth rate, however, the coefficient (-0.1831), although negative, is insignificant. A similar pattern of results arises in columns (4) and (5) when the export-weighted industry-specific exchange rate (xer) is introduced in levels form and growth rate, with a similar sized coeffcient (-0.3654) for the level of the exchange rate that is significant at 10%, and in columns (6) and (7) when the import-weighted exchange rate (mer) is introduced with a coefficient of -0.2528 that is significant at 5%.

In Table 5.17, I present the results of robust, two-way fixed effects OLS estimates for those firms whose primary industry is classified as having a lower degree of overall exchange rate exposure. In column (1), I present the estimated coefficient sums for the baseline regression without an exchange rate variable. Minimization of the BIC suggests that six, zero and two lags are appropriate for the user cost growth, sales growth and cash flow to capital ratio, respectively. Again, I find a shorter duration of the accelerator when classifying the firms by lower exchange rate exposure. Five of the seven industries in this sub-sample are also non-durables. The estimated coefficient sums for the user cost and accelerator are similar to those of the previous individually divided low exposure sub-samples in terms of sign, magnitude, and level of significance. The estimated coefficient sum on the cash flow variable, though positive, is insignificant. The number of firms in this sub-sample (444) accounts for only 17% of the firms from the full sample, which suggests that publicly-traded firms are less likely to operate primarily in industries with the least amount of external orientation.

Again, I test the exchange rate effect in levels and growth rates, using all three measures of the industry-specific real exchange rate. In columns (2) and (3) of Table 5.17, I introduce the total trade weighted industry-specific exchange rate (ter) in levels form and growth rate, respectively. Minimizing the BIC suggests that only the contemporaneous value of the exchange rate should be included for either specification, and the estimated sums for the accelerator and cash flow coefficients are practically unchanged after introducing the exchange rate. The estimated sums for the user cost coefficients, however, display a bit more variation in their point estimates than in previous analyses. When the total trade weighted industry-specific exchange rate is included in levels, its estimated coefficient (0.0068) is positive, very small, and insignificant. When it is included as a growth rate, the coefficient (-0.2118) is negative, of a similar order of magnitude to previous results, and also insignificant. When the export-weighted industry-specific exchange rate (xer) is included in levels or the growth rate (columns (4) and (5), respectively), the coefficients are both negative

Table 5.17. Two-way FE OLS: Low Overall Exchange Rate Exposure

		ter		*xer*		*mer*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta UC_{i,t}/UC_{i,t-1}$							
$\sum_{h=0}^{6} \alpha_h$	-0.7868***	-0.7812***	-0.8471***	-0.8029***	-0.9065***	-0.6889***	-0.7383***
	(-3.72)	(-3.77)	(-6.37)	(-3.83)	(-3.85)	(-3.00)	(-3.33)
$\Delta S_{f,t}/S_{f,t-1}$	0.1030**	0.1026**	0.1029**	0.1020**	0.1028**	0.1027**	0.1022**
	(1.95)	(2.03)	(2.04)	(2.03)	(2.04)	(2.03)	(2.02)
$CF_{f,t}/\hat{K}_{f,t-1}$							
$\sum_{h=0}^{2} \gamma_h$	0.0941	0.0940	0.0940	0.0943	0.0939	0.0934	0.0941
	(1.50)	(1.50)	(1.51)	(1.50)	(1.51)	(1.50)	(1.51)
$e_{i,t}$		0.0068		-0.1459		0.1785	
		(0.05)		(-0.84)		(1.47)	
$\Delta e_{i,t}/e_{i,t-1}$			-0.2118		-0.3408		0.1884
			(-1.00)		(-1.38)		(1.37)
Observations	3,713	3,713	3,713	3,713	3,713	3,713	3,713
Number of firms	444	444	444	444	444	444	444
Time horizon	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010	1995-2010
within-R^2	0.0411	0.0410	0.0411	0.0412	0.0415	0.0413	0.0411
$\hat{\sigma_\nu}$	0.2277	0.2280	0.2278	0.2273	0.2290	0.2310	0.2287
$\hat{\sigma_\epsilon}$	0.2700	0.2700	0.2700	0.2700	0.2700	0.2700	0.2700
ρ	0.4156	0.4162	0.4158	0.4148	0.4184	0.4227	0.4178

Notes: Standard errors are robust to arbitrary heteroskedasticity and autocorrelation. t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and insignificant. When the import-weighted industry-specific exchange rate (mer) is included in levels or the growth rate (columns (6) and (7), respectively), however, the coefficients are both positive and insignificant.

The contrast in results between the high and low overall exposure sub-samples provides the strongest evidence so far that the net effect of the exchange rate on investment is generally negative and works through the channel of liquidity constraints for firms in the industries that have high exchange rate exposure by all three criteria. Once again, this negative exchange rate effect is dependent upon the degree of international exposure faced by the firms.

5.3 Conclusion

This section begins with some conclusions about my findings in regard to estimating firm level investment functions. I highlight potential shortcomings of previous investment studies, and pinpoint important differences that arise from using recent data. I then discuss the conclusions that result from extending previous work on investment into an open economy setting with the inclusion of the exchange rate.

First, my results suggest that using the standard time-varying weighted measure of the user cost creates unnecessary endogeneity issues for investment equation analysis. In addition, the bias associated with using the time-varying weighted measure increases when faced with the relatively recent decline in information technology equipment and computer-based capital assets. Fixed-weighted user cost measures also contain a bias as one gets farther away from the chosen base year, and using a chain-type user cost index can help to overcome these issues. In addition, by using a chain-type user cost index, I consistently find evidence that the user cost elasticity is highly significant and negative, but significantly less than one in absolute value. Since my data and time period of analysis considerably overlap with that of Spatareanu (2008), her findings of a mostly insignificant user cost elasticity are likely due to the mismeasurement bias associated with a time-varying weighted user cost.

Second, as shown in Table 5.8, when using a chain-type user cost index and accounting for time-specific effects, the estimates for the user cost elasticity have a very narrow range of -0.5543 to -0.5615 for the full sample of U.S. manufacturing firms, even after controlling for any exchange rate effects on investment. This range of estimates indicates a larger user cost elasticity (in absolute value) than the -0.25 found in Chirinko et al. (1999). As explained in the replication section, however, I discovered some problems with the econometric methods of that study, which may have caused such a low estimate. On the other hand, my user cost estimates are very much inline with the range of -0.372 to -0.540, as found in Chirinko et al. (2011). When analyzing different sub-samples determined by the type and degree of international exposure, the range of estimates for the user cost elasticity does widen. In fact, all of the sub-samples that indicate a high degree of exposure in some form have a range of estimates for the user cost elasticity (with or without controlling for the exchange rate) of -0.5037 to -0.5911, which is similar to the range of estimates for the full sample. The range of user cost elasticity estimates for all of the sub-samples indicating a low degree of international exposure is -0.6585 to -0.8726. It is only in these sub-samples where the 95% confidence interval contains the theoretical value of negative one, as assumed in many studies using Cobb-Douglas production functions.

Next, I find that by using information criteria to determine the structure of the distributed lag model, one can gain insight into how the accelerator differs between groups of firms that operate in different competitive spheres. As is found throughout most of the investment function literature, my estimates for the accelerator are always positive and significant with at least 95% confidence. What I discover, though, is that the duration of the acclerator effect is shortened for all the sub-samples classified as having a low degree of international exposure. In these sub-samples the information criteria suggest that number of lags for the sales growth variable should include only the contemporaneous value (and up to one lag for the high import penetration sub-sample); as a result, the estimates for the accelerator are smaller for these firms with a range of 0.102 to 0.1419. Many of the industries with lower exchange rate exposure include non-durables, and it is also possible that the firms with lower external orientation operate primarily in industries that are stagnant or in decline. In addition, the results for the estimated sum of cash flow coefficients for the low export share and low imported input share sub-samples range from 0.0845 to 0.0879 and all are significant at 1%. These cash flow estimates are the largest in magnitude and most significant across all of the firm level analyses, which suggests that these firms are the most financially constrained.

Outside of the low export-oriented and low imported input reliant sub-samples, the estimated sum of coefficients for the cash flow is typically very small and/or insignificant, which is very different from the results of Chirinko et al. (1999) where the range of estimates is 0.265 to 0.511. My results, however, are more similar to those of Spatareanu (2008) where the range of estimates is 0.021 to 0.140. The time period of this analysis (1995-2010) and that of Spatareanu (2008) (1985-2001) are more recent than that of Chirinko et al. (1999) (1981-1991), which suggests that cash flow type liquidity constraints may have become less important in recent years. Not only does the time period of my analysis include the rapid decline in computer-based capital assets and an overall expansion in international trade, but also it includes a rapid expansion of financial market activity. As large, publicly-traded firms, the firms in this analysis already have greater access to capital markets than their privately-owned peers. The increased financialization of the U.S. economy over the period of this analysis may make it less likely that these firms experience financially constrained investment.

In regard to the original question of what is the effect of the exchange rate on investment in U.S. manufacturing firms, the answer is that it depends. First, it should be clear that any exchange rate effects on firm level investment are dependent on the type and degree of international exposure faced by the firm. Although pooling all publicly traded U.S. manufacturing firms yields insignificant results for all three industry-specific measures of the real exchange rate, I consistently find that the exchange rate does have a significant effect on investment decisions for firms in industries that have a high degree of external orientation. In addition, the evidence explaining the channels by which the exchange rate affects investment is more varied for publicly-traded firms than that found in industry level analysis of Chapter 4. In addition, the estimates for the user cost, accelerator, and cash flow coefficient sums are very stable after introducing the exchange rate in all of the separate analyses.

The most convincing evidence supports a significant negative effect of the level of the real value of the dollar on investment that is comparable in order of magnitude (in terms of the absolute value of the corresponding elasticities) to the accelerator and user cost effects in most of the estimates for the firms that have relatively high international exposure. This effect is found to be statistically significant with a 95% confidence level for the firms that operate primarily in industries with a high overall level of exchange rate exposure and in those facing a high level of import penetration. In these sub-samples, the level of both the total trade and import-weighted industry-specific real exchange rates are significant at 5%. In the sub-sample with a high overall level of exchange rate exposure, the coefficient on the level of the export-weighted real exchange rate is also significant, but only at 10%. The range of estimates in both of these sub-samples for the exchange rate effect is fairly narrow at -0.2455 (*mer* for high import penetration) to -0.3727 (*ter* for high overall exposure). In comparison, Blecker (2007) finds a range of -0.17 to -0.26 for the long-run coefficients on the level of the broad, trade-weighted real value of the dollar in his aggregate analysis of U.S. manufacturing.

Following Blecker (2007), I have referred to the level of the real exchange rate as affecting investment through the channel of financial or liquidity constraints, but this may not be the best way to think about it. In the closed economy investment literature, a firm has a desired capital stock, and a lower level of internal funds (cash flow or cash) may prevent the firm from investing as much as it wants to in order to reach that desired capital stock. This dynamic is at the heart of using the level of the cash flow in order to find evidence of financially constrained investment. The point that should be taken, though, is that a variable entered in levels form essentially acts upon the speed (or rate) of investment undertaken by the firm in order to meet its desired capital stock. In the context of exchange rates, it may be better to think of the level of the real value of the dollar as a signal to firms that provides information as to whether the current exchange rate environment is conducive to following through with their planned investment. In the case of the firms in the sub-samples with high overall exposure or a high degree of import penetration, a higher level of the real value of the dollar may indicate a less conducive environment for investment; as a result, these firms may slow the rate at which they invest in capital goods.

On the other hand, I also find evidence that the exchange rate can have a large, negative effect on the desired capital stock. For the firms in the sub-samples classified as having a high export share or a high reliance on imported inputs, it is the growth in the real value of the dollar that has a negative and significant effect on investment (although only with 90% confidence), which suggests that these firms reduce their desired capital stock in response to an appreciating dollar. In addition, this response is dependent upon how the real value of the dollar is weighted, with only the total trade and import-weighted real exchange rates (ter and mer) showing statistical significance. The range of estimates for the coefficient on the growth of the real value of the dollar is -0.3356 to -0.2302, which suggests that the exchange rate effect on the desired capital stock for these firms is of a similar order of magnitude as the effect of the user cost and accelerator.

Overall, the majority of the evidence presented in this chapter suggests a large and significant negative effect of the real value of the dollar on investment in the U.S. manufacturing sector for firms with a high degree of international exposure in one form or another. Whether this effect operates upon the desired capital stock or upon the rate of investment is dependent upon the type and degree of exchange rate exposure.

CHAPTER 6

CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

This study has produced new estimates of the effects of the real value of the U.S. dollar on domestic investment by U.S. industries and firms in the manufacturing sector, which is the sector that accounts for the vast majority of U.S. trade in goods. The study uses both industry-level and firm-level panel data sets and estimation techniques optimized to each data set, which are applied to models based on two different theoretical frameworks, in order to produce a complementary set of estimates that can test the robustness of the results. Moreover, the study uses updated and improved data sets compared to previous research, and also takes advantage of current state-of-the-art methods in the estimation of econometric models using panel data. In addition to the estimates of exchange rate effects, this study also yields new and often different results for the effects on investment of the other variables that are controlled for, including sales growth (the "accelerator effect"), the cost of capital (both interest rates and the theoretically preferred "user cost"), and corporate cash flow (representing possible financial or liquidity constraints), compared with previous research.

The industry-level part of the study takes the modeling approach of Campa and Goldberg (1999) as a benchmark for the analysis. Extensive replication efforts fail to reproduce the exact results of that study, possibly (at least in part) as a result of the use of new and revised data (even for the same time period originally covered in that article). In addition, I find that the results of estimating their model are sensitive to various aspects of the specification, that the authors likely corrected for the wrong departures from classical least squares assumptions, and that overall their original results for the U.S. manufacturing sector were quite fragile. Nevertheless, Campa and Goldberg's work remains an important benchmark because they developed a now-standard theoretical model of exchange rates and investment that has been used in various other studies (although none for the United States since their original work). Campa and Goldberg pioneered a modeling framework that interacts the real exchange rate with the inverse of the average industry markup (which they treated as endogenous) and with two different indicators of the degree of international exchange rate exposure: the share of exports in industry sales and the estimated share of imported inputs in industry costs. Theoretically, a higher real value of the dollar should have a negative effect on an industry's desired capital stock, and hence on its investment expenditures, when interacted with the export share and a positive effect when interacted with the imported input share, and the net impact of a rise in the dollar's value through both of these channels is ambiguous (*i.e.*, it is an empirical question whether the net impact is positive or negative).

Contrary to the original findings of Campa and Goldberg, I do not find any evidence of a statistically significant positive effect of the dollar's value on investment via the imported input cost channel, either in the replications of their sample period or using my extended data set (which goes up to 2005). This result is somewhat surprising, given that my data set includes years when the share of imported inputs increased notably in many industries and the dollar also varied considerably in value. In contrast, I do find robust evidence of a negative effect of the dollar's value on investment when the exchange rate is interacted with the export share. In my extensions of Campa and Goldberg's methodology, I find that these negative effects are more often significant in high-markup industries, whereas those authors originally found these effects to be more significant in low-markup sectors. I also use split samples according to the degree of import competition in goods markets (measured by the share of imports in domestic consumption) and find that the negative effects of a higher dollar are more significant in industries with a high degree of import penetration, although somewhat paradoxically this effect is strongest when the exchange rate is weighted by the industries' export shares.

In addition, I provide the first estimates of U.S. investment behavior using the industry-level real exchange rate indexes originally developed by Goldberg (2004) and now provided by the Federal Reserve Bank of New York. In these estimates, I do not attempt to identify the separate channels through which the exchange rate can affect investment, but rather seek to determine the overall, net effect using three alternative measures (real exchange rates weighted by exports, imports, and total trade). These estimates show evidence of large and significant negative net effects of the real value of the dollar on investment expenditures using the real exchange rates weighted by industry-level total trade and by exports, but not using import weights. Overall, and in spite of some variations depending on the model specifications and econometric techniques used, the preponderance of evidence suggests that the negative impact of a higher dollar on investment through diminished competitiveness of exports in global markets generally outweighs any possible positive impact that could arise via cheaper imports of intermediate inputs at the industry level. Of course, nothing in this study denies that the latter (i.e., cheaper imported inputs) may have a positive impact on industry profits, but such a positive impact on profits (if it exists) does not seem to translate into greater investment in U.S. productive capacity.

As noted above, the Campa and Goldberg (1999) approach is based on a rigorous microeconomic model of investment determination assuming profit maximization by firms. Although this approach has the strength of grounding their empirical work in an explicit theoretical framework and carefully identifying the various channels for exchange rate effects on investment, it also has the weakness that it imposes significant restrictions on the econometric estimation that could possibly bias the results. Among other things, their theoretical model leads to the use of only a single annual lag for all the right-hand side variables in the investment equation, whereas much of the broader literature on investment (which does not include exchange rate effects) has found long and variable lags in the effects of the independent variables (including cost of capital, the accelerator, and cash flow). In addition, Campa and Goldberg's model focuses exclusively on how the exchange rate and other explanatory factors affect investment via their impact on the desired capital stock and ignores the potential for financial or liquidity constraints to limit the current flow of investment relative to any given level of desired capital stock, as has been recognized in a significant branch of the investment literature. The need to interact the real exchange rate with both markups and indicators of external exposure introduces additional possible sources of bias or measurement error, and can make the overall results difficult to interpret. Finally, there are some peculiarities in Campa and Goldberg's empirical approach, including the use of a simple interest rate rather than a broader measure of the cost of capital and the fairly unusual inclusion of oil prices in an investment function as a proxy for input costs. These considerations lead to the use of a more conventional and open-ended modeling approach that imposes less *a priori* restrictions, and which is more consistent with the broader literature on investment functions, in the firm-level portion of the present research.

As discussed in Chapter 2, a much larger literature on investment functions has coalesced (in spite of some dissents) on a general framework based on accelerator effects, the user cost of capital (which incorporates the costs of equity finance, the impact of tax policy, and changes in the relative prices of different capital goods in addition to interest rates), and cash flow (as a proxy for possible liquidity constraints). This framework does have theoretical underpinnings in the literature on the "flexible accelerator" from the 1960s, and the work of Robert Eisner and others who rejected the restrictive assumption of a Cobb-Douglas technology that constrained the effects of the first two variables to be equal and opposite in sign (because of the strong assumption of a unitary elasticity of substitution). The financial or liquidity constraint component of this approach also has a long theoretical pedigree ranging from Kalecki (1937) to Stiglitz and Weiss (1981) and Minksy (1986), and is supported by numerous empirical studies including Fazzari et al. (1988) and Chirinko and Schaller (1995), among others, as cited in Chapter 2. I use the study by Chirinko et al. (1999) as a benchmark for this empirical modeling approach, which is quite open-ended in terms of both the lag structure and the unrestricted magnitudes of the estimated coefficients. This dissertation is the first study that I am aware of that tests for exchange rate effects on U.S. investment at the firm level by including exchange rates in a model of the type used by Chirinko et al. (1999).[1]

Implementing the empirical approach of Chirinko et al. (1999) led me into a considerable detour regarding the measurement of the user cost of capital for my my more recent sample period.[2] Most previous studies of this type, including Fazzari et al. (1988) and Spatareanu (2008) in addition to Chirinko et al. (1999), used time-varying weights in constructing the relative price of capital goods to output, which is an important element in the user cost formula. Such an approach did not seem to cause many problems in time periods when the relative prices of different capital assets did not change very much. However, I discovered that when this methodology is applied to the data for the 1990s and early 2000s, when prices of computers and other information technology-based capital assets were declining dramatically, the use of time-varying weights led to an anomalous failure of the user cost measure to show any comparable decrease. The likely reason for this anomaly is that the demand for such assets is price-inelastic, so that the increases in the quantities of those assets are proportionately smaller than the decreases in their prices, resulting in decreasing shares of those assets in the total value of capital assets. If these changing shares are used as time-varying weights on the asset prices, the result is to put a continuously decreasing weight on the assets whose

[1] A partial exception is Blecker (2007), who included the exchange rate in this type of model for the aggregate U.S. manufacturing sector, but did not use firm-level micro data.

[2] It should be noted that, although the user cost data are used in the firm-level regression analysis, the user cost variable is constructed at the industry level. See Chapter 3 for more details.

prices are falling the most, and hence to remove the consequences of those price declines from the aggregated relative price of capital goods for each industry.[3]

To eliminate this bias, I tested both fixed weights and chain-type indexes, and concluded that the latter are the best measures and the least susceptible to introducing bias into the estimates. Fixed weight indexes have the opposite bias from time-varying weights, which is that they exaggerate the effects of the price declines by not allowing any changes in the weights as quantities adjust, and they are known to become increasingly unreliable as one moves further away from the base year. In contrast, chain weights use geometrically averaged information for each pair of adjacent years to generate an ideal index that more accurately reflects the true change in user cost over time for each industry. Among other things, I show that using chain weighted user cost eliminates the evidence for endogeneity of this variable (or any other right-hand side variable) and thereby permits the use of OLS with two-sided fixed effects for consistent panel data estimation of the firm-level investment function.

Compared to the previous studies using this framework, my results for the control variables are as follows. For the user cost, my best estimates of this elasticity are on the order of about -0.55 (for firms in industries with high international exposure), which is larger (in absolute value) than the estimates of about -0.25 in Chirinko et al. (1999), but my estimated elasticity is still significantly less (again in absolute value) than the value of unity implied by the approach of Hall and Jorgenson (1967) who imposed the assumption of Cobb-Douglas technology. My user cost elasticity is closer in magnitude to the more recent estimates of Chirinko et al. (2011). For accelerator effects, I find that these are generally strong and significant and of similar orders of magnitude to previous studies—sometimes even greater—although the precise results do vary in different subsamples of firms according to the degree of international exposure in their corresponding industries. For cash flow, I find that the estimated coefficients are generally smaller (often an order of magnitude smaller) than in Chirinko et al. (1999) and most of the previous literature (with the exception of Spatareanu (2008), who also found that these coefficients had diminished), and are often insignificant or at best significant at the 10% level. This latter result may be attributed to the greater development of financial markets in recent decades, which may have relieved liquidity constraints on firms' investment finance—especially for the publicly traded companies included in

[3]The bias from using time-varying asset weights in constructing user cost with more recent data is a possible explanation for the results of Spatareanu (2008), whose estimated user cost elasticities were generally small and insignificant and sometimes had the wrong (positive) sign.

my dataset. However, I also found that cash flow effects are larger and more significant in some subsamples, especially for firms in industries with low export shares.

I introduce the exchange rate into my baseline firm-level model using the Chirinko et al. (1999) framework in two alternative ways. Following the logic of the modified flexibile accelerator model with liquidity constraints, any variable that affects the desired capital stock should enter the investment equation in differences or growth rate form, as is the case with the user cost and sales (both of which are entered as percentage changes), because investment is a flow variable related to the *change* in the capital stock. However, variables that affect the current flow of investment—*i.e.*, the rate at which firms actually increase their capital stocks in moving toward the desired levels—should enter the equation in levels form, as is commonly done for cash flow (on the theory that liquidity constraints affect the flow of investment rather than the desired capital stock). This distinction was also utilized by Blecker (2007), who found more evidence of significant exchange rate effects on investment in the aggregate U.S. manufacturing sector using the real exchange rate in levels rather than percentage changes, and therefore concluded that the primary channel for the influence of the exchange rate on investment is via tightening or relaxing financial constraints.

My results using this estimation strategy were mixed, but mostly tended to identify negative effects of a higher dollar on investment for firms in industries that are relatively open to international markets by various indicators. I did not find any significant effects of the real exchange rate on investment in the full sample of firms for all manufacturing industries, either in levels or in growth rates. It was only when I split the samples by indicators of exchange rate exposure in the firms' primary industries (by two-digit SIC) that significant effects of the exchange rate emerged for firms in the industries with relatively high degrees of such exposure. Also, some of the results were sensitive to which of the three measures of industry-level real exchange rates (weighted by total trade, exports, or imports) were used, with generally more significant results using the total trade and import weights in the firm-level estimates. When ranking industries by export shares and shares of imported inputs, I found that the rate of change in the real value of the dollar has a significant negative effect on investment in firms in industries with relatively high export shares or imported input shares, indicating that a rising value of the dollar tends to diminish investment in such firms by decreasing their desired capital stocks.

However, when I split the sample according to the degree of import penetration in goods markets (import shares of domestic consumption) and by overall exchange rate exposure (industries ranking high or low on all three measures—export shares, imported input shares, and import penetration ratios), I found that the *level* of the real exchange rate had a significant negative effect on investment for firms in industries that ranked highly by all three criteria. These latter results are more similar to those of Blecker (2007) in regard to the level of the exchange rate, rather than its rate of increase, affecting the flow of investment. These latter results could be consistent with a liquidity constraints channel for exchange rate effects, or could simply indicate that firms in those industries tend to postpone planned investment expenditures when the dollar is high and speed them up when the dollar is low. For firms in industries with low degrees of exchange rate exposure by any of these measures, exchange rate effects were generally insignificant in either levels or growth rates, with the exception of some anomalously positive coefficients (in both levels and growth rates) on import-weighted exchange rates for firms in industries with low shares of imported inputs in their costs. With these few exceptions, I did not find any evidence of significant positive effects of the value of the dollar on investment by U.S. manufacturing firms, especially (and most notably) in the industries that rank highest in shares of imported inputs.

Overall, in both the industry-level and firm-level estimates, I found that the effect of the real value of the dollar on U.S. manufacturing investment is mostly negative (when it is statistically significant) in a wide variety of models, but the precise effects are dependent upon the type and degree of international exposure faced by domestic producers as well as on the exchange rate measure used and various other elements in the specification (for example, the weighting of the exchange rate in the Campa and Goldberg approach). This finding is particularly pronounced in the firm-level estimates, in which the exchange rate effect was only unmasked in the firms with a high degree of international exposure in one form or another, but the industry-level estimates were also sensitive to various aspects of the specifications and subsamples used. Overall, these findings suggests that there are important industry and firm level characteristics that are ignored in studies performed at the aggregate level, and which are important for understanding how the exchange rate affects investment behavior.

In contrast to some previous studies (especially Campa and Goldberg, 1995, 1999), I find little evidence of a positive effect of a higher value of the dollar on investment through the channel of the cost of imported intermediate goods. The lack of a significant role for the exchange rate to affect investment through the cost channel is quite surprising given the steady rise in the imported input share for most U.S. manufacturing industries, as shown in Chapter 3. The period of investigation in this study includes the era of the globalization of production and the accompanying explosion in international trade. In general, the results suggest that the exchange rate has a greater impact on domestic fixed capital formation via its effect on the competitiveness of manufactured goods in both domestic and export markets than through its effect on the cost of imported intermediate inputs. Or, to put it another way, even if U.S. manufacturing producers benefit from cheaper imported inputs (and may increase their offshoring of production) in response to a dollar appreciation, the net impact of such an appreciation on those producers' investments in U.S. manufacturing capacity still appears to be negative.

The question of whether the real value of the dollar is more likely to affect desired capital stocks or the rate of investment spending (via liquidity constraints or otherwise) is still unclear. The industry level results of this study show robust evidence that the declining competitiveness of manufacturers in export markets when the dollar appreciates negatively affects desired capital stocks, but this was in a modeling framework that only allowed for effects on desired capital stocks. The firm level results, in contrast, suggest that the channel through which the exchange rate influences investment (via desired capital stocks or the pace of investment spending) varies depending upon the type and degree of international exchange rate exposure. Additional research that tests the effect of the level of the real value of the dollar on industry-level investment is necessary to augment the results of this study.

This brings me to the limitations of the present study and potential directions for future research. One important limitation is the admittedly imperfect nature of the estimated shares of imported inputs in total costs, which as explained in Chapter 3 are based on very strong assumptions. Research at both the firm and industry levels could benefit from improved measures of these shares, but at present the finely grained data on the use of imports that would be necessary to improve these measures do not appear to be available. Otherwise, in regard to the industry-level estimation, perhaps the most important extension of the present research would be to consider a wider spectrum of U.S. industries in addition to the manufacturing sector covered here. Although other industries do not export as much, they may rely more on imported intermediate goods, or even (as in the case of transportation and wholesale and retail trade) could potentially benefit from cheaper imports of finished goods. Thus, some of the qualitative results for manufacturing investment found here may not be found in other industries, so this would be an important extension of the analysis.

For the firm-level estimation, one important consideration is that it remains to be determined whether the exchange rate might influence investment indirectly via other included variables such as sales growth and cash flow, in addition to the direct effects of the exchange rate found here. In the estimates in Chapter 5, various lags of the other variables remained significant when the exchange rate was included, while no lags of the exchange rate were ever significant. Further research is required to test whether possible lagged effects of the exchange rate are already captured in those other variables and their lags, in which case the total impact of the exchange rate (direct and indirect) would be greater than what was found here. One way to approach this would be to test for endogeneity of sales growth and cash flow with respect to the exchange rate, perhaps through simultaneous equations methods or other econometric approaches. Another alternative, more in the spirit of Blecker (2007), would be to use aggregate GDP growth rather than industry-specific sales growth to pick up accelerator effects, and then see if the estimated exchange rate effects (both contemporaneous and lagged) become larger or more significant.

In addition, some issues arise from the inclusion of industry-level data in firm-level panel regressions. Especially, it is difficult to draw conclusions about publicly-traded firms using industry-level measures of exchange rate exposure, especially when these firms make up only a small fraction of the total number of U.S. manufacturing firms.[4] Although much of the firm-level data on export sales in Compustat is missing or incomplete, it would be interesting to see if a smaller sample of firms could be investigated using this data. In addition, a firm-level user cost could be constructed using the firm's weighted average cost of capital instead of common estimate for each industry.

Finally, it would also be helpful to reconcile the results of this study regarding the role that exchange rates may have on investment through the pricing and markup decisions of a firm with the findings of the exchange rate pass-through literature (*e.g.* Feinberg (1989) and Fisher (1989)). The model of Campa and Goldberg (1999) attempted to make this connection, but failed to incorporate the way in which markups could influence cash flows and liquidity constraints as considered by Blecker (2007). Combining theory from the exchange rate pass-through and financial constraints literatures may provide a better framework for detecting whether liquidity constraints on investment could be influenced by exchange rate effects on profit margins. Empirically, additional extensions regarding liquidity constraints would include investigating subsamples defined by the degree of financial friction faced by firms (for example, splitting the sample by higher or lower cash flow or other indicators) and interacting the exchange rate with proxies for financially constraints, as was

[4]The number of firms in my sample in 2005 is 1,755 compared to the 288,500 manufacturing firms with paid employees according to the U.S. Census Bureau's Survey of Current Business Owners in 2007 (the survey year closest to 2005). Of course, the publicly-traded firms probably account for a somewhat higher proportion of total output than they do of total firms.

done in the study of U.K. firms by Leonida et al. (2006). I look forward to investigating these types of issues in future research.

REFERENCES

Allayanis, G. and A. Mozumdar (2004). "The investment-cash flow sensitivity puzzle: can negative cash flow observations explain it?" *Journal of Banking and Finance* 28, 901–930.

Arellano, Manuel (1988). "An alternative transformation for fixed effects models with predetermined variables." Applied Economics Discussion Paper 57, Institute of Economics and Statistics, University of Oxford.

Arellano, Manuel and Stephen Bond (1991). "Some tests of specification for panel data: Monte carlo evidence and an application to employment equations." *Review of Economic Studies* 58, 277–297.

Arellano, Manuel and Olympia Bover (1995). "Another look at the instrumental variable estimation of error-components models." *Journal of Econometrics* 68, 29–51.

Bahmani-Oskooee, Mohsen and Massomeh Hajilee (2010). "On the relation between currency depreciation and domestic investment." *Journal of Post Keynesian Economics* 32(4), 645–660.

Bartelsman, Eric J. and Wayne Gray (1996). "The NBER manufacturing productivity database." Technical Working Paper 205, National Bureau of Economic Research.

Baum, Christopher F. (2001). "Residual diagnostics for cross-section time series regression models." *The Stata Journal* 1(1), 101–104.

Baum, Christopher F. (2006). *An Introduction to Modern Econometrics Using Stata*. College Station, TX: Stata Press.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman (2003). "Instrumental variables and GMM: Estimation and testing." *The Stata Journal* 3, 1–31.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman (2007). "Enhanced routines for instrumental variables/generalized method of moments estimation and testing." *The Stata Journal* 7(4), 465–506.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman (2010). "ivreg2: Stata module for extended instrumental variables/2SLS, GMM estimation and AC/HAC, LIML and k-class regression.

Beck, Nathaniel and Jonathan N. Katz (1995). "What to do (and not to do) with time-series cross-section data." *The American Political Science Review* 89(3), 634–647.

Beveridge, S. and C. Nelson (1981). "A new approach to the decomposition of economic time series into permanent and transitory components." *Journal of Monetary Economics* 33, 5–38.

Bischoff, Charles W., Barry Bosworth, and Robert Hall (1971). "Business investment in the 1970s: a comparison of models." *Brookings Papers on Economic Activity* (1), 13–63.

Blecker, Robert A. (2007). "The economic consequences of dollar appreciation for US manufacturing investment: A time-series analysis." *International Review of Applied Economics* 21(4), 491–517.

Bond, Stephen (2002). "Dynamic panel data models: A guide to micro data methods and practice." Working Paper CWP09/02, Cemmap, The Institute for Fiscal Studies.

Bosworth, Barry P. (1993). *Saving and Investment in a Global Economy.* Brookings Institute Washington, DC.

Brainard, William C. and James Tobin (1968). "Pitfalls in financial model building." *The American Economic Review* 58(2), 99–122.

Caglayan, Mustafa and Rebeca Munoz-Torres (2008). "The effects of the exchange rates on investment in Mexican manufacturing industry." Warwick Economic Research Paper No. 846, Department of Economics, The University of Warwick, Coventry, England.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller (2006). "Robust inference with multi-way clustering." Technical Working Paper 327, National Bureau of Economic Research.

Campa, José and Linda Goldberg (1995). "Investment in manufacturing, exchange rates and external exposure." *Journal of International Economics* 38, 297–320.

Campa, José and Linda Goldberg (1997). "The evolving external orientation of manufacturing: A profile of four countries." Technical report, Federal Reserve Bank of New York Economic Policy Review.

Campa, José and Linda Goldberg (1999). "Investment, pass-through, and exchange rates: A cross-country comparison." *International Economic Review* 40(2), 287–314.

Chirinko, Robert S. (1993). "Business fixed investment spending: Modeling strategies, empirical results, and policy implications." *Journal of Economic Literature* 31(4), 1875–1911.

Chirinko, Robert S. and Robert Eisner (1983). "Tax policy and investment in major U.S. macroeconomic econometric models." *Journal of Public Economics* 20(2), 139–166.

Chirinko, Robert S., Steven M. Fazzari, and Andrew P. Meyer (1999). "How responsive is business capital formation to its user cost?: An exploration with micro data." *Journal of Public Economics* 74(1), 53–80.

Chirinko, Robert S., Steven M. Fazzari, and Andrew P. Meyer (2011). "A new approach to estimating production function parameters: The elusive capital-labor substitution elasticity." *Journal of Business and Economic Statistics* 29(4), 587–594.

Chirinko, Robert S. and Huntley Schaller (1995). "Why does liquidity matter in investment equations?" *Journal of Money, Credit and Banking* 27(2), 527–548.

Choi, In (2001). "Unit root tests for panel data." *Journal of International Money and Finance* 20(2), 249–272.

Clarida, Richard and Jordi Gali (1994). "Sources of real exchange-rate fluctuations: How important are nominal shocks?" *Carnegie-Rochester Conference Series on Public Policy* 41, 1–56.

Cleary, Sean (1999). "The relationship between firm investment and financial status." *The Journal of Finance* 54(2), 673–692.

Cleary, Sean, Paul Povel, and Michael Raith (2007). "The U-shaped investment curve: Theory and evidence." *Journal of Financial and Quantitative Analysis* 42(1), 1–39.

Cummins, Jason G., Kevin A. Hassett, and R. Glenn Hubbard (1994). "A reconsideration of investment behavior using tax reforms as natural experiments." *Brookings Papers on Economic Activity* (2), 1–74.

Domowitz, Ian, R. Glenn Hubbard, and Bruce C. Peterson (1986). "Business cycles and the relationship between concentration and price-cost margins." *RAND Journal of Economics* 17, 1–17.

Driscoll, J. and A. C. Kraay (1998). "Consistent covariance matrix estimation with spatially dependent data." *Review of Economics and Statistics* 80, 549–560.

Eisner, Robert (1969). "Tax policy and investment behavior: Comment." *American Economic Review* 59(3), 379–388.

Eisner, Robert (1970). "Tax policy and investment behavior: Further comment." *American Economic Review* 60(4), 746–752.

Eisner, Robert and M.I. Nadiri (1968). "Investment behavior and neo-classical theory." *Review of Economics and Statistics* 50(3), 369–382.

Fazzari, Steven M. (1993). "Monetary policy, financial structure, and investment." In Gary A. Dymski, Gerald Epstein, and Robert Pollin, eds., *Transforming the US Financial System: Equity and Efficiency for the 21st Century*, pp. 35–63. ME Sharpe Armonk, NY.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Peterson (1988). "Financing constraints and corporate investment." *Brookings Papers on Economic Activity* 1988(1), 141–206.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Peterson (2000). "Investment-cash flow sensitivities are useful: A comment on Kaplan and Zingales." *The Quarterly Journal of Economics* 115(2), 695–705.

Feenstra, Robert C. (1996). "U.S. imports, 1972-1994: Data and concordances." Working Paper 5515, National Bureau of Economic Research.

Feenstra, Robert C. (1997). "U.S. exports, 1972-1994: With state exports and other U.S. data." Working Paper 5990, National Bureau of Economic Research.

Feenstra, Robert C., John Romalis, and Peter K. Schott (2002). "U.S. imports, exports and tariff data, 1972-1994." Working Paper 9387, National Bureau of Economic Research.

Feinberg, Robert M. (1989). "The effects of foreign exchange movements on U.S. domestic prices." *The Review of Economics and Statistics* 71(3), 505–511.

Fingleton, Eamonn (1999). *In praise of hard industries.* Orion Business London.

Fisher, Eric (1989). "A model of exchange rate pass-through." *Journal of International Economics* 26, 119–137.

Gilchrist, Simon and Charles P. Himmelberg (1995). "Evidence on the role of cash flow for investment." *Journal of Monetary Economics* 36(3), 541–572.

Goldberg, Linda S. (1990). "Measuring external openness: The index of effective exposure." Economic Research Report RR-90-19, C.V. Starr Center for Applied Economics, New York University, New York, New York.

Goldberg, Linda S. (1993). "Exchange rates and investment in United States industry." *Review of Economics and Statistics* 75(4), 575–588.

Goldberg, Linda S. (2004). "Industry-specific exchange rates for the United States." Technical report, Federal Reserve Board of New York Policy Review.

Hall, Robert E. and Dale W. Jorgenson (1967). "Tax policy and investment behavior." *American Economic Review* 57(3), 391–414.

Hansen, Alvin H. (1938). *Full Recovery or Stagnation?* Norton New York.

Harchaoui, Tarek, Faouzi Tarkhani, and Terence Yuen (2005). "The effects of the exchange rate on investment: Evidence from Canadian manufacturing industries." Working Paper 2005-22, Bank of Canada, Ottawa, Ontario, Canada.

Harrod, Roy F. (1936). *The Trade Cycle.* Oxford University Press London.

Hodrick, Robert and Edward Prescott (1997). "Postwar U.S. business cycles: An empirical investigation." *Journal of Money, Credit and Banking* 29, 1–16.

Hoechle, Daniel (2007). "Robust standard errors for panel regressions with cross-sectional dependence." *The Stata Journal* 7(3), 281–312.

Hoyos, Rafael E. De and Vasilis Sarafidis (2006). "Testing for cross-sectional dependence in panel-data models." *The Stata Journal* 6, 482–496.

Hubbard, R. Glenn (1998). "Capital-market imperfections and investment." *Journal of Economic Literature* 36(1), 193–225.

Huizinga, John (1987). "An empirical investigation of the long-run behavior of real exchange rates." *Carnegie-Rochester Conference Series on Public Policy* 27, 149–214.

IMF (2011). "World and country notes." International financial statistics, International Monetary Fund.

Jorgenson, Dale W. (1963). "Capital theory and investment behavior." *American Economic Review* 53(2), 247–259.

Kalecki, Michael (1937). "The principle of increasing risk." *Economica* 4(16), 440–447.

Kaplan, Steven N. and Luigi Zingales (1997). "Do investment-cash flow sensitivities provide useful measures of financing constraints?" *The Quarterly Journal of Economics* 112(1), 169–215.

Kaplan, Steven N. and Luigi Zingales (2000). "Investment-cash flow sensitivities are not valid measures of financing constraints." *The Quarterly Journal of Economics* 115(2), 707–712.

Keynes, John Maynard (1936). *The General Theory of Interest, Employment and Money.* Macmillan London.

Kmenta, Jan (1997). *Elements of Econometrics* (2 ed.). Ann Arbor, MI: The University of Michigan Press.

Landefeld, Steven J. and Robert P. Parker (1997). "BEA's chain indexes, time series, and measures of long-term economic growth." *Survey of Current Business* 77(5), 58–68.

Landon, Stuart and Constance Smith (2007). "Investment and the exchange rate: Short run and long run aggregate and sector-level estimates." MPRA Paper No. 9958, Munich Personal RePEc Archive.

Leonida, Leone, Aydin Ozkan, and F. Gulcin Ozkan (2006). "Financial constraints, investment and exchange rates: Evidence from UK firms." Working paper, Department of Economics, University of York.

Levin, Andrew, Chien-Fu Lin, and Chia-Shang Chu (2002). "Unit root tests in panel data: asymptotic and finite-sample properties." *Journal of Econometrics* 108, 1–24.

Minsky, Hyman P. (1977). "The financial instability hypothesis: an interpretation of Keynes and an alternative to "standard" theory." *Challenge* 20(1), 20–27.

Minsky, Hyman P. (1984). *Can "it" happen again?: Essays on instability and finance.* ME Sharpe Armonk, NY.

Minsky, Hyman P. (1986). *Stabilizing an unstable economy.* Yale University Press New Haven, CT.

Newey, Whitney K. and Kenneth D. West (1987). "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix." *Econometrica* 55, 703–708.

Newey, Whitney K. and Kenneth D. West (1994). "Automatic lag selection in covariance matrix estimation." *Review of Economic Studies* 61, 631–653.

Nucci, Francesco and Alberto F. Pozzolo (2001). "Investment and the exchange rate: An analysis with firm-level panel data." *European Economic Review* 45(2), 259–283.

Orhangazi, Ozgur (2008). "Financialisation and capital accumulation in the non-financial corporate sector: A theoretical and empirical investigation on the US economy: 1973-2003." *Cambridge Journal of Economics* 32, 863–886.

Parks, R. (1967). "Efficient estimation of a system of regression equations when disturbances are both serially and contemporaneously correlated." *Journal of the American Statistical Association* 62(318), 500–509.

Pesaran, M.H., A. Ullah, and T. Yamagata (2008). "A bias-adjusted LM test of error cross section independence." *Econometrics Journal* 11, 105–127.

Peterson, Mitchell A. (2009). "Estimating standard errors in finance panel data sets: Comparing approaches." *Review of Financial Studies* 22(1), 435–480.

Phillips, Peter C.B. and Hyungsik R. Moon (1999). "Linear regression limit theory for nonstationary panel data." *Econometrica* 67, 1057–1111.

Phillips, Peter C.B. and Pierre Perron (1988). "Testing for a unit root in time series regression." *Biomètrika* 75(2), 335–346.

Prapassornmanu, Pichittra (2009). "The effect of exchange rates on firm's investment: The evidence from Thailand's manufacturing firms." Master of economics, Thammasat University, Bangkok, Thailand.

Ravn, Morten O. and Harald Uhlig (2002). "On adjusting the Hodrick-Prescott filter for the frequency of observations." *Review of Economics and Statistics* 84, 371–380.

Reed, Robert W. and Haichun Ye (2011). "Which panel data estimator should I use?" *Applied Economics* 43(7-9), 985–1000.

Roodman, David (2009). "How to do xtabond2: An introduction to difference and system GMM in Stata." *The Stata Journal* 9(1), 86–136.

Salinger, Michael A. and Lawrence H. Summers (1983). "Tax reform and corporate investment: A microeconometric simulation study." In Martin Feldstein, ed., *Behavioral Simulation Methods in Tax Policy Analysis*, pp. 247–281. Chicago: University of Chicago Press.

Samuelson, Paul A. (1939a). "Interactions between the multiplier analysis and the principle of acceleration." *Review of Economics and Statistics* 21, 75–78.

Samuelson, Paul A. (1939b). "A synthesis of the principle of acceleration and the multiplier." *Journal of Political Economy* 47, 786–797.

Samuelson, Paul A. (1959). "Alvin hansen and the interactions between the multiplier analysis and the principle of acceleration." *Review of Economics and Statistics* 91, 183–84.

Schonberger, Richard J. (2001). *Let's Fix It!: Overcoming the Crisis in Manufacturing.* Simon & Schuster New York.

Schott, Peter K. (2008). "The relative sophistication of Chinese exports." *Economic Policy* 23(53), 5–49.

Spatareanu, Mariana (2008). "The cost of capital, finance and high-tech investment." *International Review of Applied Economics* 22(6), 693–705.

Steindel, Charles (1995). "Chain-weighting: The new approach to measuring GDP." *Current Issues in Economics and Finance* 1(9), 1–6.

Steindl, Josef (1952). *Maturity and stagnation in American capitalism.* Blackwell Oxford.

Stewart, Ricky L., Jessica Brede Stone, and Mary L. Streitwieser (2007). "U.S. benchmark input-output accounts, 2002." *Survey of Current Business* 87(10), 19–48.

Stiglitz, Joseph E. and Andrew Weiss (1981). "Credit rationing in markets with imperfect information." *The American Economic Review* 71(3), 393–410.

Swift, Robyn (2005). "The changing external exposure of Australian industry." *The Australian Economic Review* 38(3), 253–264.

Swift, Robyn (2007). "Exchange rate implications for Australian manufacturing investment and exports." *Economic Analysis & Policy* 37(2), 145–162.

Thompson, Samuel B. (2009). "Simple formulas for standard errors that cluster by both firm and time." Working paper, Arrowstreet Capital, L.P.

Tobin, James (1969). "A general equilibrium approach to monetary theory." *Journal of money, credit and banking* 1(1), 15–29.

Tobin, James (1978). "Monetary policies and the economy: the transmission mechanism." *Southern Economic Journal*, 421–431.

Triplett, Jack E. (1992). "Economic theory and BEA's alternative quantity and price indexes." *Survey of Current Business* 72(4), 49–52.

Veblen, Thorstein (1917). *The Theory of Business Enterprise.* Charles Scribner's Sons New York.

Windmeijer, Frank (2005). "A finite sample correction for the variance of linear efficient two-step GMM estimators." *Journal of Econometrics* 126, 25–51.

Wooldridge, Jeffrey M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2 ed.). Cambridge, MA: The MIT Press.

Worthington, Paula R. (1991). "Investment, GNP and real exchange rates." *Economic Perspectives* 15(4), 2–10.